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TESIS DOCTORAL

ESSAYS ON INFORMATION TRANSMISSION IN FINANCIAL MARKETS

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Resumen en Castellano

El trabajo de investigación realizado para la obtención del grado de Doctor en Economía se compone de tres trabajos en dos áreas de Economía Financiera, Finanzas Corporativas y Valoración de Activos, con fundamentos teóricos de la Microeconomía. El primer capítulo analiza el papel de los directores "interlocking" (directores presentes en los consejos de administración de dos empresas diferentes de manera simultanea) como transmisores de información durante la selección de potenciales empresas objetivo en los procesos de fusion y adquisicion. El segundo capítulo es un trabajo conjunto con José M. Marín. En este capítulo analizamos el contenido de la información de los "drawdowns" (depreciación del fondo desde su máximo histórico) de hedge funds (fondos de inversión libre) y sus implicaciones en la cartera. El tercer capítulo analiza el papel de las reuniones de los consejos de administración en la adquisición de información de los directores externos.

Capítulo 1: Directores Interlocking y Seleccion de Empresas Objetivo en las Fusiones y Adquisiciones

Este capítulo investiga el papel de los directores "interlocking" en la resolución de los problemas de información asimetría en las fusiones y adquisiciones. Desarrollo un modelo de información privada que predice que tener un director interlocking con el adquirente aumenta la probabilidad de ser seleccionado entre los potenciales adquiridos. De acuerdo con el modelo, se demuestra que las empresas interlocking tienen más probabilidades de ser seleccionados como adquiridos, en particular cuando hay una mayor asimetría de la información en parte del adquirido, o cuando el adquirente esta financieramente limitado. Además, el modelo predice que la empresa interlocking que no esta seleccionada tendra rendimientos bajos. De acuerdo con esta predicción, documento que las empresas interlocking no seleccionadas tienen bajos rendimientos posteriores con respecto a sus pares. Por último, se muestra que ese fenómeno de la mayor probabilidad de adquirir una empresa interlocking no se debe a explicaciones alternativas, como la centralidad de la red, o atrincheramiento de los gestores. En general, la evidencia sugiere que los directores interlocking mitigan ineficiencias que surgen de asimetrías de información en las fusiones y adquisiciones.

Capítulo 2: Análisis de los Drawdowns de los Hedge Funds: Calidad de la Gestión, Aseguramiento al Mercado y Selección Darwiniana

En este capítulo analizamos el estado de "drawdown" de los hedge funds como una característica de los hedge funds relacionada con su rendimiento-riesgo. El "estado de drawdown" de un hedge fund es definido como el decil al que pertenece el drawdown del fondo en la distribución de la industria (en un momento dado en el tiempo). La teoría económica sugiere que tanto el nivel actual como la evolución pasada del estado de drawdown de un fondo son características relacionadas con varias variables claves de los fondos, incluyendo el talento del gestor y el nivel de seguimiento por parte de los inversores, y, por tanto, son predictivas del rendimiento futuro del fondo. El análisis da lugar a cuatro resultados completamente novedosos sobre los hedge funds. En primer lugar, el uso extensivo de estrategias de aseguramiento al mercado hace que carteras de los fondos que exhiben pequeños drawdowns tengan rendimientos bajos, en general, y muy pobres, en tiempos de crisis. En segundo lugar, el mercado opera un proceso de selección darwinista según el cual los fondos que sufren grandes drawdowns durante un período de tiempo prolongado (los supervivientes) tiendan a estar administrados por gestores talentosos que producen rendimientos futuros excepcionales. En tercer lugar, el análisis aflora una nueva dimensión del riesgo que surge como un rasgo distintivo de los hedge funds: alto riesgo condicional a supervivencia es equivalente a rendimiento excepcional. En cuarto lugar, el análisis del estado de drawdown plantea serias dudas sobre el papel jugado por otras características de los hedge funds –como la Delta Total– sobre el rendimiento de los fondos y hace dudar sobre la validez de algunas de las medidas de evaluación de la calidad de la gestión –como el ratio de Calmar y el de Sterling– ampliamente utilizados por los profesionales.

Capítulo 3: ¿Qué Aprenda Directores Externos en las Reuniones de los Consejos de Administración?

Este trabajo analiza el contenido de la información que los directores externos adquieren en las reuniones de los consejos de administración. Encuentro que los directores externos significativamente incrementan sus transacciones en acciones de la empresa después de las reuniones. Los directores externos obtienen rendimientos anormales de sus compras cuando estas se realizan justo antes o después de las reuniones del consejo. El rendimiento es significativamente mayor en los casos donde la transacción se inicia después de la reunión. Los directores externos que compran acciones de la compañía antes de las reuniones no tienen mejor rendimiento que los ejecutivos, mientras los que compran después de las reuniones obtienen mayores rendimientos en comparación con sus homólogos ejecutivos. Sin embargo, de acuerdo con la literatura, las transacciones de venta, a diferencia de las de compra, no parecen ser causadas por una mejor información. En general, los resultados sugieren que las reuniones del consejo son importantes para la adquisición de información de los directores externos, y, por tanto, un elemento importante de sus funciones de supervisión y asesoramiento a los directivos.

Contents

Chapter 1

Introduction

This thesis consists of three papers on information transmission and processing in financial markets. It combines topics from two areas of Financial Economics, Corporate Finance and Asset Pricing, with theoretical grounds from Microeconomics. The first chapter analyzes the role of interlocking directors as information transmitters in target selection in mergers and acquisitions. The second chapter analyzes the information content of hedge fund drawdowns and its portfolio implications. The third chapter analyzes the role of board meetings in outside directors' information acquisition.

In the first chapter, entitled *Interlocking Directors and Target Selection in Mergers and Acquisitions*, I analyze the role of interlocking directors in resolving the problems that arise from information asymmetry between the parties involved in M&As. Interlocking directors are directors that sit on the boards of both the target and the acquirer at the time of the deal announcement. Due to their position, these directors are privy to important information on both firms, and therefore, stand as a distinguished channel of *private information transmission.* This is a central feature in the model I develop.

To motivate my empirical tests, I develop a simple *model of target selection within an information asymmetry context.* In this model, the acquirer receives private information on one of the targets. Empirically, this corresponds to acquirers obtaining target-specific information through interlocking directors. The model has two basic predictions that are testable. 1. *The firms that have an interlocking director with the acquirer are more likely to be selected as targets.* This prediction has strong empirical support; interlocking directors raise the likelihood of becoming a target by 12.18 percentage points. The effect is particularly strong for targets that experience poor past performance, that are small, that are risky, or that belong to a different industry; which are precisely the targets that invoke greater information asymmetry problems for the acquirer. Similarly, acquirers that have high financial leverage, or insufficient cash holdings, or limited liquidity are further biased towards interlocking targets. This is consistent with these acquirers' willingness to use stock as the payment method, which leads to information asymmetry problems that operates against targets. To the extent that the above cases are those where target or acquirer-specific information is more valuable, results indicate that *interlocking directors have a significant role in transmitting private information that is critical to target choice.*

Modeling target selection as a function of private information provides another prediction which is, perhaps, even more interesting. 2. *If the acquirer selects a non-interlocking firm in the presence of an interlocking potential target, this non-selected interlocking firm will under-perform its peers through time.* The intuition is that this case occurs only when the private information of the acquirer corresponds to negative news on this target. By comparing the post-deal accounting performance of the non-selected interlocking firms with that of their peers, I find empirical support for their poor performance. I also document that the portfolios of non-selected interlocking firms under-perform a number of alternative portfolios.

The second chapter is a joint work with José M. Marín. In this chapter, entitled *On the Economics of Hedge Fund Drawdown Status: Performance, Insurance Selling, and Darwinian Selection*, we analyze information transmission and processing in the world of hedge funds, with a focus on *drawdowns.* Drawdowns are losses from the peak point of any investment. In a strong contradiction to simple intuition and industry performance evaluation trends, we find that *hedge funds that survive prolonged periods of large drawdowns are managed by truly talented managers who deliver outstanding performance.* We explain this phenomenon by the market's *Darwinian selection mechanism* where investors keep the funds managed by talented managers alive, and let the others die. The essence of Darwinian mechanism lies in two features: 1. Better *information transmission* from the fund managers to the investors, as these managers would be willing to disclose more on their investment philosophy to rationalize the large drawdown. Not doing so would probably result in the exit of investors and the death of the fund. 2. Better *information processing* of fund investors, as it is most worthwhile to analyze extra relevant information about the manager's investment philosophy after large drawdowns. The reason is the *high water mark clause* specific to the hedge fund world that prevents investors from paying fees until the fund returns to the its peak investment point. Investors who stay in the fund would save a lot of fees, but this is reasonable only when the expected return of the fund is positive; that is, when the manager is talented. Consequently, an investment strategy that forms a portfolio of highest drawdown funds delivers a monthly risk-adjusted return of 1.23 percent.

On the contrary to the outstanding performance of the highest drawdown funds, we document the poor performance of the lowest drawdown funds in this study. This is driven by the heavy presence of *insurance sellers* in low drawdown portfolios. These are funds managed by untalented traders who specialize in strategies akin to selling insurance, which share the property of delivering positive returns in normal times but have the hidden cost of large losses during crises periods. As a result, we find that *low drawdown funds are weak performers, in general, and bad performers in times of turmoil.*

In the third chapter, entitled *What Do Outside Directors Learn At Board Meetings?*, I analyze the information content of annual *board meetings* from the point of view of *outside directors*. Board meetings are important events for not only the decisions taken during them, but also for the substantial information gathering taking place in advance. To assess their information value, I study the extent of insider trading around board meetings, along with traders' performance. Three observations arise from the study: 1. Outside directors *significantly increase their trade after the board meetings.* 2. The abnormal returns to outside directors purchases are positive around the board meetings, and significantly higher for cases *where the trade is initiated after the meeting.* 3. Outside directors who purchase company stock before the board meetings do not have better performance than the executives, whereas those who trade after the board meetings gain significantly higher market adjusted returns as *compared to their executive counterparts*. These results are consistent with the view that board meetings are important in outside directors' information acquisition: Outsider directors do learn a lot about their firms at annual board meetings. Consequently, meetings are useful in bridging the information gap between the inside and outside members of the board.

Consistent with the literature, insider sales provide modest evidence on that they are information driven. Outside directors who sell their company stock after the board meetings perform better than those who sell before, even though the effect is small and not highly significant. Overall, the results in this study suggest that board meetings provide valuable information to outside directors, and therefore, are an important element of their advising and monitoring duties.

Chapter 2

Interlocking Directors and Target Selection in Mergers and Acquisitions

2.1 Introduction

The board of directors plays a very important role in mergers and acquisitions. Both the target firm's and acquirer firm's board of directors are decisive at the stages of selection, bidding and deal consummation. It is a very interesting phenomenon that in many deals, some board members contemporaneously sit on the boards of the target firm and the acquirer firm, yet our knowledge of these interlocking directors' effect is quite limited. This paper explores the role of interlocking directors in target selection in mergers and acquisitions (M&As) within an information asymmetry context.

A well documented friction in the M&A market, inspired by Akerlof (1970) and put forward by Hansen (1987), is information asymmetry regarding the target value: Target knows more about its value than the bidder. This results in an *adverse selection* problem, where bids are only accepted by targets with values less than or equal to the bid. Consequently, bidder faces an *overpayment cost* that is increasing in the value of the bid. Fishman (1989) notes that this leads to an efficiency problem because value-increasing bidders may be deterred from making offers.

Dual to the target-side information asymmetry, M&As induce information asymmetry regarding the bidder value: Bidder knows more about its value than the target (Hansen 1987). When bidder uses its equity to finance the acquisition, this results in an *adverse selection* problem. The reason is that raising equity to finance investments might be perceived by outside markets as an attempt to sell a lemon since firms would prefer to use their stock when it is overvalued (Myers and Majluf 1984). Hence, the use of equity rather than cash as means of payment would indicate a low valuation of the bidder stock, resulting in, as Eckbo, Giammarino, and Heinkel (1990) puts it, a *bidder undervaluation cost*.

Interlocking directors sit on the boards of the target and the acquirer firm during the acquisition process. Due to their position, they are privy to important information both about the target and about the acquirer firm. This access to information, along with the availability of direct communication with other decision makers (board members), makes interlocking directors a distinguished channel of information transmission between the parties involved in M&As. A straightforward question arises from this discussion: *Do interlocking directors, by communicating their privileged information during the M&A process, help resolve the information asymmetry problems explained above*? This paper attempts to answer this question.

I start by developing a simple model of target selection based on asymmetric information. The model's first prediction is that in most cases, the bidder will select the target on which she has private information. To test this implication, I examine the extent to which bidders (acquirers) select the *interlocking firms* in actual M&As. I define the interlocking firms as all potential target firms that have at least one current director that is contemporaneously sitting on the board of the acquirer. I presume that these directors serve as a channel of private information transmission. Consistent with the model, I find that firms that have an interlocking director with the acquirer (interlocking firms) are more likely to be selected among potential target firms. The economic significance of the relation between interlocking directors and target selection is substantial. Conditioning on firms with similar industry and size characteristics, having an interlocking director with the acquirer raises the likelihood of becoming a target by 12 percent. The effect is robust across various industry classifications and firm characteristics that are used to define the set of potential targets.

As a next step, I document that interlocking director effect is more pronounced when information asymmetry in the target environment is greater, which implies a greater *overpayment cost* for the bidder. The increase in the probability of becoming a target is higher when targets are smaller, when targets experience worse past performance, or when targets have higher standard deviation of monthly stock returns. To the extent that private information is likely to be more valuable for targets with greater information asymmetries, this finding suggests that interlocking directors are better able to exploit their informational advantage when targets have opaque information environments. Interlocking director effect is also more pronounced when the bidder and the target are from different industries, which implies greater information asymmetry between the bidder and the target, but not necessarily a more opaque environment for the target. Moreover, I find that target premium paid by the acquirer is significantly smaller in interlocking deals. All these findings are consistent with the hypothesis that interlocking directors help resolve informational asymmetry problems regarding the target value.

In addition to target-specific information, interlocking directors may play a role in transmitting bidder-specific information. The method of payment (cash versus equity) in M&As has important consequences for the information revealed by the bidder and the target; hence for the deal outcome.[1] Many factors play a role in determining the method of payment in acquisitions. Cash offers may mitigate the adverse selection problem caused by acquirer's private information on her own stock. However, they may also exacerbate the adverse selection problem caused by target's information advantage in target valuation. Equity payment offers an advantage in limiting the overpayment cost by making the target partake in the bidder's gains and losses, whereas also introducing a bidder undervaluation cost.[2] Tax issues are important factors as well, the amount of

[1] See Hirshleifer (1995) for an in-depth analysis.

[2] The bidder faces a tradeoff between the likelihood of paying too much, or of offering too little and

equity and cash effects the tax shield and timing of the acquisition. For all these reasons, it is not clear which method of payment the acquirer would prefer in M&As. However, financially constrained firms are unlikely to easily raise capital, hence might be obliged to choose equity financing. If we believe that these constrained firms will necessarily use their stock to finance acquisitions, we would expect such firms to select a target that knows better about its valuation so as to avoid the *bidder undervaluation cost*. Indeed, I find that acquirers are more likely to select interlocking targets when they are highly leveraged, or cash-strapped, or constrained in liquidity. This is consistent with the hypothesis that interlocking directors help resolve informational asymmetry problems regarding the acquirer value.

Modeling target selection as a function of private information provides a second prediction. According to the model, if the private information on an interlocking potential target is negative, the bidder will select the non-interlocking target as long as the synergy value is above some threshold. Therefore, in an actual merger, if a non-interlocking target is selected when an interlocking potential target firm exists, we can infer that the private information regarding the interlocking firm is negative; or, at least, weaker than that for the other potential target firms. We would expect the negative news about the interlocking firm to come out after some time. I test this hypothesis and find support for this prediction as well. I document that interlocking firms, that are not selected in deals where a non-interlocking target is selected, have worse post-deal announcement performance with respect to their peers. This is observed through a deterioration in the accounting and stock market performance of the non-selected interlocking firms. This provides further evidence on the idea that informational superiority of the interlocking director benefits the bidder in selecting an appropriate target.

As a final step, I test for alternative explanations that could generate similar empirical patterns and show that the main results still hold. For example, an interlocking firm may be more likely to be chosen as a target simply because this firm is more central in the network of directors; hence the existence of interlocks. More central firms, due to their

being rejected. Equity makes the terms contingent on the target's value, hence target shares some of the overpayment cost with the bidder.

busy directors, may under-perform (Fich and Shivdasani 2006) and tend to become takeover targets (Barber, Palmer, and Wallace 1995; Cremers, Nair, and John 2009; Hasbrouck 1985; Morck, Shleifer, and Vishny 1988). If this were the first order effect, then controlling for busy directors would make the interlocking director effect disappear. Another possible explanation of the empirical facts may come from the entrenchment theory (Bebchuk, Cohen, and Ferrell 2009; Gompers, Ishii, and Metrick 2003). According to this theory, the interlocking directors might facilitate merger process not because of informational reasons, but because they act as negotiators so as to prevent anti-takeover defenses. If this were the case, first, we would expect a strong presence of anti-takeover defense measures in these potential targets. Second, under this explanation, interlocking director effect would be stronger for highly entrenched target firms. Finally, we would expect that controlling for corporate governance variables weakens the results regarding the interlocking directors. I show that these alternative explanations are not supported by the data.

This paper contributes to the literature by shedding new light on the role of the interlocking directors in M&As. The literature has traditionally focused on the effect of network centrality on firm actions and performance, where network centrality is defined with respect to interlocking directors. For example, **?** show that central firms do better performing acquisitions. They also find that central firms are more likely to use cash, to make an acquisition, and to be acquired. Stuart and Yim (2010) document that firms that have interlocking directors with firms that previously experienced a private equity deal are more likely to receive private equity offers. Similarly, Bouwman and Xuan (2010) find that a firm is more likely to engage in M&As, among other financial activities, if it has interlocking directors with firms that engage in the same activity. However, these papers focus on the transmission of experience and know-how through interlocking directors; they do not consider target or acquirer-specific information as they do not look at the direct connection between the actual target and acquirer. This paper, on the contrary, considers the transmission of firm-specific information that is critical to target choice.

This paper further contributes to the M&A literature by introducing a model of target selection in a private information context. The theoretical literature on merger decisions is ample; numerous studies extend the traditional theories of mergers based on transaction costs (Coase 1937), hubris (Roll 1986), agency costs of free cash flow (Jensen 1986), and managerial entrenchment (Shleifer and Vishny 1989). Recent studies develop models that combine different theories. For instance, Gorton, Kahl, and Rosen (2007) combine elements from agency theory and q theory (Jovanovic and Rousseau 2002) to argue that mergers can be used as defensive mechanisms to avoid being acquired or as positioning mechanisms to become attractive takeover targets. Rhodes-Kropf and Robinson (2008) revisit property rights theory (Hart and Moore 1990) and use search, scarcity, and asset complementarity to explain merger decisions. Nevertheless, the significance of private information in merger decisions has been overlooked.[3] In my model, one party (the acquirer) has private information on the valuation of the other party (one of the targets). To the best of my knowledge, this is the first study that models target selection in such private information context, and provides empirical evidence on it.

Finally, this paper contributes to the growing literature on takeover premiums. Song and Walkling (2000) demonstrate the increase in firms' stock prices following the acquisition of their rivals and attribute this to the increased expectation that they will be taken over themselves. Consistent with this, I find that the portfolios of potential target firms experience price increases and obtain economically and statistically significant alphas. In that, my paper is related to Cremers, Nair, and John (2009) who show that anticipated takeovers affect the correlation of a stock's return with the market return. They construct a quintile-spread portfolio that buys firms with a high takeover vulnerability and sells firms with a low takeover vulnerability and demonstrate the abnormal returns associated with it. The alphas reported in this paper are consistent with what they obtain from the quintile-spread portfolio (an annualized 14-19% vs. 12%). However, whereas Cremers, Nair, and John (2009) determine firms from probit regressions run each year using all available firms, I focus on the firms that are similar to the actual targets during portfolio formation.

[3] I refer to private information on the *counterparty*. The literature mostly attributes private information to the party itself, i.e., firms have private information on their own stand-alone values or synergy contributions; agents have private information on their own abilities, projects or firms.

The most relevant study to this paper is that of Cai and Sevilir (2012) who examine the *performance* of *completed* M&A transactions between firms with interlocking directors. Unlike the previously mentioned studies, they analyze the transactions where there is a direct board connection between the parties involved in M&A. They find that acquirers significantly obtain higher announcement returns in interlocking deals; and relate this to the acquirer's ability to pay lower takeover premiums and lower advisory fees in such transactions. Although Cai and Sevilir (2012) suggest that acquirer's information advantage can explain the empirical facts, they do not have information asymmetry variables in their study. My finding that higher information asymmetry regarding the target value significantly increases the effect of the interlocking directors complements their study.

The paper is organized as follows. First, I build a model of target selection and derive its empirical implementation. This is presented in Section 2.2. Section 2.3 describes the data and offers some descriptive evidence. Section 2.4 analyzes the impact of interlocking directors on the probability of becoming a target, with an emphasis on information asymmetry. Section 2.5 discusses the effect of interlocking directors on deal structure. The performance of non-selected interlocking firms are analyzed in Section 2.6. Robustness checks are provided in Section 2.7. Section 2.8 concludes.

2.2 Empirical Research Design

2.2.1 The Model

In this section, I present a simple model that motivates my empirical tests. The model is based on the idea that the interlocking directors provide an important channel for information transmission between the parties involved in M&As.

The model has three strategic players: One bidder and two potential targets. Targets can be of two possible types. One type, which I refer to as *high-value target*, has a stand-alone value of v_H, while the other type, referred to as *low-value target*, has a stand-alone value of v_L, where $v_L < v_H$. The likelihood that the target is of high-value type is q. I assume that the merger creates a synergy value of $w > 0$, which does not depend on the type of the target.

The sequence of events is as follows. At $t = 0$, targets' types are determined independently from each other and targets learn their own types. At $t = 1$, bidder receives a private signal on the type of one of the targets, which I refer to as the *acquainted target*. Similarly, since the bidder does not have private information on the other target, I will label it as the *unacquainted target*. The signal, $\eta \in h, l$ has quality $1/2 < \phi < 1$, defined as $\phi = Pr(\eta = h|v_H) = Pr(\eta = l|v_L)$.[4] I assume that making an offer is costless; but the bidder can make at most one acquisition offer. At $t = 2$, bidder submits a take it or leave it offer with price p to one of the targets; or does not make an offer. If the bidder does not submit an offer, the game ends. If the bidder submits an offer, at $t = 3$, the selected target's board accepts or rejects the offer, and the game ends.

First, note that bidder's ex-ante valuations of both targets is the same: $E[v_1] = E[v_2] = \overline{v} = qv_H + (1-q)v_L$. Upon observing the private signal, bidder forms a posterior on the type of the acquainted target by Bayesian updating. Specifically:

$$Prob(v_1 = v_H|\eta = h) = \frac{q\phi}{q\phi+(1-q)(1-\phi)} = \Phi_H$$

$$Prob(v_1 = v_L|\eta = h) = 1 - \Phi_H$$

$$Prob(v_1 = v_L|\eta = l) = \frac{(1-q)\phi}{(1-q)\phi+(q)(1-\phi)} = \Phi_L.$$

$$Prob(v_1 = v_H|\eta = l) = 1 - \Phi_L$$

If the bidder offers $p < v_L$, no potential target will accept the offer. So, we can restrict our attention to offer prices where $p \geq v_L$ without loss of generality. Note also that the synergy value is positive, so the bidder will always submit an offer, even though the offer price may be low.

To solve the model, I proceed by backward induction and obtain the expected profits from optimum offers to each potential target. It is straightforward to start with the un-

[4] The signal is imperfect, i.e. $\phi < 1$. In the case of perfect signal, the acquirer always selects the acquainted target, makes an offer equivalent to the stand-alone value of the target and obtains profits equal to the synergy value.

acquainted target as the bidder does not receive any private signal regarding this target, hence there is no Bayesian updating. The profit maximizing bid for the unacquainted target and expected profits are summarized in the below lemma.

Lemma 1. *If the bidder selects the unacquainted target:*
(i) If $\frac{w}{v_H - v_L} \geq \frac{(1-q)}{q}$*, the bidder will offer* $p = v_H$ *and obtain expected profits of* $w - [(1-q)(v_H - v_L)]$*.*
(ii) Otherwise the bidder will offer $p = v_L$ *and obtain expected profits of* $(1-q)w$*.*

Proof. See Appendix 1. ■

Intuitively, the bidder has to compare the benefits and the costs of bidding. A high bid induces high probability of success, hence higher expected *synergy gains* (w). However, it also implies high expected *overpayment cost* ($v_H - v_L$) since bids are only accepted by targets with values less than or equal to the bid. When the synergy value is high relative to the cost of overbidding, the acquisition is attractive for the bidder. The bidder is less cautious about overbidding, and submits a high value offer to realize the synergy gains. When the synergy value is relatively low, overbidding is too costly; and the bidder submits a low value offer.

Note that I characterize the optimum offer with respect to the ratio of the synergy value to the difference between high and low valuations, i.e. $\frac{w}{v_H - v_L}$. This variable captures the *attractiveness of the acquisition* from the bidder's point of view. A bidder will bid more aggressively as the synergy value increases; or as the cost of overbidding decreases.

The analysis is more complicated for the acquainted target since the bidder receives a private signal regarding this target. After the Bayesian updating, the bidder will submit an offer depending on the signal. The profit maximizing bid for the acquainted target and expected profits are summarized in the below lemma.

Lemma 2. *If the bidder selects the acquainted target and the signal is high* ($\eta = h$)*:*
(i) If $\frac{w}{v_H - v_L} \geq \frac{(1-\Phi_H)}{\Phi_H}$*, the bidder will offer* $p = v_H$ *and obtain expected profits of*

$w-[(1-\Phi_H)(v_H-v_L)]$, where $\Phi_H=\frac{q\phi}{q\phi+(1-q)(1-\phi)}$.

(ii) Otherwise the bidder will offer $p=v_L$ and obtain expected profits of $(1-\Phi_H)w$.

If the bidder selects the acquainted target and the signal is low ($\eta=l$):

(i) If $\frac{w}{v_H-v_L}\geq\frac{\Phi_L}{(1-\Phi_L)}$, the bidder will offer $p=v_H$ and obtain expected profits of $w-[\Phi_L(v_H-v_L)]$, where $\Phi_L=\frac{(1-q)\phi}{(1-q)\phi+(q)(1-\phi)}$.

(ii) Otherwise the bidder will offer $p=v_L$ and obtain expected profits of $\Phi_L w$.

Proof. See Appendix 1. ■

The intuition is identical to the previous case, except that the private signal changes the levels of thresholds. The solution, i.e. target selection and the offer value, will be determined by a comparison of the expected profits of the bidder established in the above lemmas. I present the summary of results in the following proposition.

Proposition 1. *If the bidder receives a high signal ($\eta=h$):*

(i) If $\frac{w}{v_H-v_L}\geq\frac{1-\Phi_H}{q}$, the bidder will offer $p=v_H$ to the acquainted target and obtain expected profits of $w-[(1-\Phi_H)(v_H-v_L)]$, where $\frac{1-\Phi_H}{q}=\frac{(1-q)(1-\phi)}{q[q\phi+(1-q)(1-\phi)]}$.

(ii) Otherwise the bidder will offer $p=v_L$ to the unacquainted target and obtain expected profits of $(1-q)w$.

If the bidder receives a low signal ($\eta=l$):

(i) If $\frac{w}{v_H-v_L}\geq\frac{1-q}{1-\Phi_L}$, the bidder will offer $p=v_H$ to the unacquainted target and obtain expected profits of $w-[(1-q)(v_H-v_L)]$, where $\frac{1-q}{1-\Phi_L}=\frac{(1-q)[(1-q)\phi+q(1-\phi)]}{q(1-\phi)}$.

(ii) Otherwise the bidder will offer $p=v_L$ to the acquainted target and obtain expected profits of $\Phi_L w$.

Proof. See Appendix 1. ■

The following table illustrates the model's predictions on target selection.

	Level of attractiveness of the acquisition for the bidder $(\frac{w}{v_H - v_L})$		
	Low $(0 \rightarrow \frac{1-\Phi_H}{q})$	Medium $(\frac{1-\Phi_H}{q} \rightarrow \frac{1-q}{1-\Phi_L})$	High $(\frac{1-q}{1-\Phi_L} \rightarrow \infty)$
Low signal $(\eta = l)$	Acquainted target	Acquainted target	Unacquainted target
High signal $(\eta = h)$	Unacquainted target	Acquainted target	Acquainted target

In most of the cases, the bidder will find it more profitable to submit a bid for the *acquainted target*. The reason is that the bidder has valuable private information on the value of the acquainted target. The bidder will exploit this information in a way to maximize the expected value of the profits, which depends on the probability that the target accepts the offer. If the signal is high, the bidder will submit a high value offer; and if the signal is low, the bidder will submit a low value offer.

Only when there is a strong contradiction between the level of attractiveness of the acquisition and that of the signal, will the bidder make an offer to the unacquainted target. One case is when the acquisition is highly attractive, but the bidder receives a low signal on the valuation of the acquainted target. In this case, the synergy value is high enough to compensate for the possibility of overbidding so that the bidder wants to make a high value offer. However, as signal reveals that the acquainted target has a lower probability of being a high-value target, the bidder will find it more profitable to make an offer to the unacquainted target. Alternatively, upon receiving a high signal when the acquisition attractiveness is very low, the bidder will select the unacquainted target. In this case, the bidder will tend to make a low value offer so as to avoid relatively very high overbidding costs, and the probability of offer acceptance is higher for an offer to the unacquainted target.

2.2.2 Empirical Implementation

In this section, I describe the empirical research motivated by the model. As noted in the previous section, the model predicts that in most cases, the bidder selects the acquainted target to make an offer. Empirically, this corresponds to bidders selecting interlocking firms, as in such cases bidders are privy to important information on targets through interlocking directors. The *only* cases where the bidder selects the unacquainted target correspond to strong contradictions in the attractiveness of the acquisition and bidder's private information. Given this, I put forward the following hypothesis.

Hypothesis 1. *A bidder is more likely to select an interlocking firm among potential target firms.*

Next, I examine whether interlocking director effect is particularly strong for target firms with higher information asymmetries. Note that the noisy signal received by the acquirer reduces the information asymmetry between the target and the acquirer. When the impact of information asymmetry in target environment is more relevant, i.e. for example when $v_H - v_L$ is larger, the value of this private information will be higher. Given that interlocking directors can serve as transmitters of private information, hypothesis 2 follows.

Hypothesis 2. *The positive effect of interlocking directors on target selection will be stronger when the information asymmetry regarding the target firm is high.*

Even though the model refers to information asymmetry regarding target value, the M&A literature is also concerned with information asymmetry regarding acquirer value. My third hypothesis considers this line of research. Following insights from the literature, I conjecture that financially constrained firms are likely to be obliged to use their stock for acquisitions. In these situations, as bidder undervaluation costs will arise, being able to transmit private information on her own value to the target will benefit the bidder.

Considering interlocking directors as transmitters of such information offers the following hypothesis.

Hypothesis 3. *The positive effect of interlocking directors on target selection will be stronger when the bidder is financially constrained.*

My final hypothesis relates directly to the predictions of the model regarding the non-selected targets. Note that the model provides two cases where the bidder selects the unacquainted target. One of these cases is where the attractiveness of the acquisition is very high, however, the signal is low. The second case is where the signal is high but attractiveness of the acquisition is so low that the bidder avoids submitting a high value bid. Empirically, we observe situations where an interlocking firm looses against a non-interlocking firm in target selection. In terms of the model, either one of the two cases must hold for these situations. Given that making a bid requires the bidder to incur further costs due to advisory, reputational or other related issues; empirically, it is unlikely that the bidder submits a bid when the attractiveness of the acquisition is very low. Therefore, I conjecture that the selection of the non-interlocking firm is most likely to correspond to the case where the bidder receives a signal pointing to a low valuation of the acquainted target firm. As one would expect the negative news on the acquainted firm to come out by time, the last hypothesis follows.

Hypothesis 4. *Among the potential target firms, if the bidder selects a non-interlocking firm, the non-selected interlocking firm will under-perform its peers throughout time.*

2.3 Data and Descriptive Statistics

2.3.1 M&A and Directors Data

I obtain the initial M&A sample from the Securities Data Company's (SDC) Mergers and Acquisitions Database. Data regarding board of directors come from the Compact

Table 2.1: **Sample Selection**

This table records the detailed sample selection process. I obtain the initial M&A sample from Securities Data Company's (SDC) Mergers and Acquisitions database; data regarding directors from the Compact Disclosure CD-ROMs and Riskmetrics Directors database; the stock price data from the Center for Research in Security Prices (CRSP) daily files and company financial data from Compustat annual files.

No. of Obs. After Query	Query Description
	Machine search in SDC
	SDC Domestic M&As announced between 1/1/1996 and 12/31/2005
41,100	Deal type included: disclosed value M&As, leveraged buyouts and tender offers
40,050	Percent of shares acquirer is seeking to own after transaction: 50% or higher
40,050	Target Nation: United States
6,531	Target Public Status: Public
5,817	Acquirer Nation: United States
3,906	Acquirer Public Status: Public
3,734	Deal value is $ 5 million or higher
	Manual filtering of data
	Exclude:
3,681	Deal is intended or still pending
3,632	Self tender, division sale, bankruptcy process deals
3,505	Bidder is already a majority owner
3,412	Bidder and target have common parent company
3,408	Duplicate entries
	Merging with other databases
2,752	Both bidder and target are identified in CRSP database, matched by CUSIP or ticker and company name
2,349	Both bidder and target are identified in directors data set, matched by CUSIP or ticker and company name
2,096	Target has control variables available in the prior fiscal year end, obtained by using Compustat annual files
2,088	Target has lag return and volatility data available in prior six months, obtained by using CRSP daily files; final sample

Disclosure CD-ROMs and Riskmetrics Directors database. I obtain the stock price data from University of Chicago's Center for Research in Security Prices (CRSP) daily files; and company financial data from Compustat annual files. Table 2.1 records the detailed sample selection process.

Due to data limitation with respect to company directors, I set the sample period from January 1, 1996 to December 31, 2005 by the announcement date.[5] I require that all M&As are between U.S. public companies and that the acquirer is seeking to own at least 50% of the shares of the target company after the transaction. I only consider deals with a minimum of $ 5 million transaction value. I exclude the deals that are intended (where there is no actual bid) or deals that are still pending. I further exclude self tenders, division sales and bankruptcy process deals because these are not M&As in the traditional sense. I do not consider deals where the acquirer is already a majority owner as in these deals, target is already under the control of the acquirer. Similarly, I exclude the deals where the target and the acquirer belong to the same parent company. Finally, I delete the duplicate entries.[6] This process results in a sample of 3,408 M&As.[7]

Even though both the target and the acquirer are identified as *public* by SDC database, many companies in this M&A sample do not have data available at CRSP on the deal announcement date.[8] This is mainly due to the stock of the company being delisted from the stock exchange before the announcement date. To eliminate companies that do not have available stock market data, I merge my M&A sample with CRSP daily files. I end up with a sample of 2,752 M&As. Note that this is also a required step to later identify the U.S. public companies that are potential targets.

At this stage, I would like to identify interlocking directors between any two companies, not only for the companies in the M&A sample, but also for other similar U.S. public companies. This would enable me to match each actual bidder from the M&A sample with potential targets and assess board connections. For this purpose, I create a comprehensive data set of directors using two different sources.

My basic source of directors data is Standard and Poor's (S&P) Compact D/SEC (popularly known as Compact Disclosure) CD-ROMs. These CD-ROMS are updated

[5]I obtain data on directors from Compact Disclosure and Riskmetrics Directors databases. The intersection of these databases covers the period 1996-2005.

[6]There are four duplicate entries (SDC deal numbers: 555019020, 575222020, 656812020 and 1433365020) which are previous versions of correctly updated entries.

[7]My sample selection closely follows Luo (2005).

[8]If the deal announcement takes place on a public holiday, I replace the announcement date with the subsequent day when the markets are open.

each month, and include financials and text information extracted from 10-K reports, proxy statements and other company filings. This database covers all companies that file with the U. S. Securities and Exchange Commission (SEC) and that have assets in excess of $5 million. The relevant variables for my analysis are the name, age and title of company directors. Additionally, this database provides the same type of data on company officers, and for the reasons that will become clear in the following paragraphs, I include also officers data in my study. Compact Disclosure extracts information on directors mainly from proxy statements whereas information on officers come from 10-Ks. Since 10-K and proxies are required to be filed annually by companies, I use the June CD-ROMs to produce my data set.[9] Unfortunately the publication of Compact Disclosure CD-ROMs has been ceased in 2006, hence I set my sample period end as December 31, 2005.

My second source of directors data is Riskmetrics Directors database. This database covers mainly S&P 1500 companies from the year 1996 onwards and provides data on the identity and characteristics of board directors. Riskmetrics obtains information from annual board meetings of companies. Because they are large public companies that file with the SEC, the companies in Riskmetrics Directors database are covered by Compact Disclosure CD-ROMs. However, not all directors of Riskmetrics database are included in Compact Disclosure database as the latter database do not list all directors after some threshold number. Supplementing Compact Disclosure data with Riskmetrics data enables me to correctly classify many companies as interlocking whereas otherwise would have been classified as non-interlocking.[10] However, due to the fact that Riskmetrics provides data starting from 1996, I set my M&A sample period beginning as January

[9]This is the commonly used approach in the literature for producing data sets using Compact Disclosure CD-ROMs. For instance, Helwege, Pirinsky, and Stulz (2007) use October CD-ROMs, although they do not provide a specific reason for the choice of October. My choice of June comes from the fact that the latest available CD-ROM is of July 2006; however some July CD-ROMS are missing. For consistency, I use June CD-ROMS of each year. This also enables me to extract all available information that belongs to the calendar year 2005. I performed a manual check to see whether supplementing the data set with information from December CD-ROMs would improve the analysis, however it has appeared to have almost zero value added.

[10]Ferris, Jagannathan, and Pritchard (2003) find that the boards with directors serving on three or more boards are heavily skewed toward the largest companies in their sample, and that such directors hold approximately half of their directorships in Forbes 500 companies. Given this, it is especially important to supplement Compact Disclosure data with Riskmetrics data as directors missing in Compact Disclosure database are more likely to belong to S&P 1500 companies.

1, 1996.[11] This results in a sample period of ten years (1996-2005) that includes booms and bottoms in merger activity.

Creating a data set of directors out of these two different sources is not trivial. Compact Disclosure is not a directors database in its nature, the information provided on directors is text information, which implies that the directors do not have IDs. Hence, I perform first an automated correction and later a manual check for assignment of a unique ID to each director. Riskmetrics database, on the other hand, is directors database, hence includes a unique ID for each director. However, to be able to merge its directors data with Compact Disclosure data, I repeat the ID assignment process for the combined data set. The basic identifiers in my analysis are name, age and title for the directors; and CUSIP and ticker for the companies.

The directors data set I create covers 23,010 distinct firms, 302,808 distinct individuals, and spans the period from 1994 to 2005. I merge the M&A sample with this data set. A total of 2,349 deals, which is 85.3% of the whole sample, have information on both the target and the acquirer directors in the year prior to the deal announcement. To be more precise, I use a 450 days window prior to the announcement date to identify the directors from the company filing information provided by Compact Disclosure.[12] The choice of the window comes from Fahlenbrach, Low, and Stulz (2010) who define adjacent proxies as to have a maximum of 450 days in between. This choice is also appropriate for Riskmetrics data set as annual meetings almost always take place in the same month of each year.

I control for several target characteristics that may affect target selection. For this reason, I exclude the deals where one or more of the target financial controls in the fiscal year prior to the announcement date are not available from Compustat annual files. Finally, I consider only the deals where the target lagged six months return and volatility data prior to the announcement date is available from CRSP daily files as these

[11] Actually, I need one year of prior data to determine the interlocking directors. However, given that Riskmetrics database provides 84% of 1996 directors data during the first half of the year, I opt to include 1996 M&A data in my study. I supplement the directors data set with Compact Disclosure's 1994-1995 data.

[12] This is the precise reason for the inclusion of director data that pertains to year 1994. However, note that only last three months of 1994 data will be relevant.

are included in my control variables.

Table 2.2: **M&A Sample by Announcement Year and Deal Type**

This table presents the distribution of the M&A sample by announcement year and presence of an interlocking director. *Interlocking deal* is a deal in which there exists at least one director that is common to both the target and the acquirer. *Non-interlocking deal* is a deal in which there exists no such common director.

	Number of All M&A Deals	Number of Interlocking Deals	Number of Non-Interlocking Deals	All Deals % Over Years
1996	223	9	214	10.68
1997	289	11	278	24.52
1998	297	9	288	14.22
1999	299	10	289	14.32
2000	259	13	246	12.40
2001	206	13	193	9.87
2002	109	3	106	5.22
2003	135	3	132	6.47
2004	144	2	142	6.90
2005	127	3	124	6.08
Total	2,088	76	2,012	100.00 %

My final M&A sample consists of 2,088 deals, with an average value per transaction at $1,911 million. Table 4.2 presents the distribution of my M&A sample by the announcement year, and with respect to the presence of interlocking directors. Consistent with the literature, the merger activity in my sample drops from its peak in 1999 until 2003, where it bounds back and then decreases again gradually in 2005. I label a deal as *interlocking* if there exists at least one director common to both the target and the acquirer firm at the time of the deal announcement, and I label such directors as *interlocking directors*. A deal where there is no interlocking director is labeled as *non-interlocking.* Out of 2,088 deals, 76 (3.6%) are interlocking and 2,012 are non-interlocking. In terms of transaction values, interlocking deals represent $184,050 million (4.6%) of the overall transaction volume from 1996 to 2005.

Table 2.3 presents the industry distribution of the target and the acquirer based on the United States Department of Labor's Standard Industrial Classification (SIC) code

Table 2.3: **M&A Sample by Industry Distribution of the Target and the Acquirer**

This table presents the industry distribution of the target and the acquirer based on the United States Department of Labor's Standard Industrial Classification (SIC) code divisions. SIC code industry divisions are: Agriculture, Forestry, Fishing; Mining; Construction; Manufacturing; Transportation, Public Utilities; Wholesale, Retail Trade; Finance; and Services. The final column and row present the industry distribution of the target and the acquirer for the sample of interlocking deals.

	Acquirer Industry									
	Agricult., Forestry, Fishing	Mining	Construct.	Manufact.	Transport., Public Utilities	Wholesale, Retail Trade	Finance	Services	All Deals Total	Interlocking Deals
Target Industry										
Agriculture, Forestry, Fishing	1	0	0	2	0	0	0	0	3	0
Mining	0	53	1	13	13	2	3	0	85	7
Construction	0	0	4	0	1	1	2	0	8	0
Manufacturing	0	11	2	519	14	27	19	44	636	25
Transportation, Public Utilities	0	1	0	7	132	1	8	9	158	4
Wholesale, Retail Trade	0	0	0	40	5	79	5	20	149	11
Finance	0	0	0	7	6	3	533	17	566	8
Services	0	1	1	87	33	14	26	321	483	21
All Deals Total	1	66	8	675	204	127	596	411	2,088	76
Interlocking Deals	0	9	0	27	6	5	12	17	76	

divisions.[13] Manufacturing (30.5% of targets and 32.3% of acquirers), Services (23.1% of targets and 28.5% of acquirers) and Finance (27.1% of targets and 19.7% of acquirers) are the most active industries in the M&A sample in terms of the number of acquisitions. These are followed by Transportation & Public Utilities, Wholesale & Retail Trade, and Mining industries.[14] As can be seen in the final column and row of the table, interlocking deals do not concentrate strongly by industry and their industry distribution exhibits a pattern similar to the M&A sample.

Before moving to the next section to analyze the deal characteristics, I should clarify the specification of "interlocking deals". My aim is to identify the deals where there is a strong channel of information transmission between the parties involved in M&A. As a result, I focus on the directors who are contemporaneously sitting at the boards of the target and the acquirer. However, there are few cases where the unique interlock is not a common board director; but a *director* at the target firm, and a top-level executive at the acquirer firm. Although these cases are not identical to board interlocks, they neither are clearly distinguishable on informational grounds. The reason is that top-level executives have superior knowledge on the firm and, most likely, influence board decisions to a great extent. Consequently, I decide to specify such deals as "interlocking deals". Nevertheless, out of 76 deals, only 6 are as such; specifying these deals as "non-interlocking" does not alter the results.

2.3.2 Descriptive Statistics

In this section, I analyze the deal, target and bidder characteristics in the whole sample, and separately in interlocking and non-interlocking sub-samples. I start by reporting the descriptive statistics for the whole M&A sample in Table 2.4. Even though my sample is slightly different, the main variables are in line with those reported in the literature (Andrade, Mitchell, and Stafford 2001; Bodnaruk, Massa, and Simonov 2009; Cai and Sevilir 2012). The percentage of interlocking deals in my sample is 3.6%, as

[13]The SIC code division structure is available at the United States Department of Labor's website: http://www.osha.gov/pls/imis/sic_manual.html.

[14]The industry distribution of the targets in my sample is in line with those reported in the literature (Cai and Sevilir 2012; Kang and Kim 2008).

Table 2.4: **Descriptive Statistics for the M&A Sample**

This table presents the deal, target and acquirer characteristics for the M&A sample. Variables are defined in Appendix 2. I report the mean, median, standard deviation and interquartile range. Unless stated differently, the number of observations (N) is 2,088.

	Mean	Median	Std. Dev.	Interquartile Range
Deal				
Interlocking Dummy	0.04			
Success Dummy	0.88			
All Cash Dummy, N=1974	0.29			
All Stock Dummy, N=1974	0.47			
Hostile Dummy	0.07			
Same Industry Dummy	0.57			
Same State Dummy	0.29			
Tech Deal Dummy	0.04			
Toehold Dummy	0.03			
Tender Offer Dummy	0.16			
Poison Pill Dummy	0.01			
Proxy Fight Dummy	0.00			
Merger Of Equals Dummy	0.03			
Target Termination Fee Dummy	0.67			
Pre-Bid Competition Dummy	0.04			
Post-Bid Competition Dummy	0.04			
Target				
Return on Equity	-0.13	0.09	2.83	0.19
Book to Market	0.67	0.55	0.71	0.49
Market Capitalization	1268.78	170.77	5099.24	575.45
Growth of Sales	0.17	0.11	0.42	0.26
Price to Earnings	12.11	13.22	94.42	22.63
Debt to Equity	1.17	0.25	18.60	0.86
Institutional Ownership	0.36	0.32	0.27	0.43
Bidder				
Return on Equity, N=1966	-0.37	0.14	18.79	0.13
Book to Market, N=1950	0.47	0.39	0.42	0.37
Market Capitalization, N=1950	13355.75	1785.01	38463.66	7820.82
Growth of Sales, N=1949	0.22	0.14	0.44	0.29
Price to Earnings, N=1949	20.72	17.15	243.44	18.25
Debt to Equity, N=1968	0.51	0.37	4.16	0.78

opposed to 3.9% in Cai and Sevilir (2012) sample.[15] The rate of deal success is 88% in my sample whereas it is 76% for Bodnaruk, Massa, and Simonov (2009). 16% of bids in my sample are tender offers compared with 14% in Cai and Sevilir (2012). The fraction of all cash deals and deals in the same industry are 29.0% and 57.3% in my sample, while they are 33.2% and 60.8% for Bodnaruk, Massa, and Simonov (2009), and 35.4% and 42.1% for Andrade, Mitchell, and Stafford (2001). 7% of deals in my sample are hostile, compared with 8% in Bodnaruk, Massa, and Simonov (2009) and Andrade, Mitchell, and Stafford (2001), and 1% in Cai and Sevilir (2012). Toeholds are present in 3% of the deals in my sample, while being present in 10% of the deals in Bodnaruk, Massa, and Simonov (2009).[16] The average target (bidder) has a market capitalization of $1,269 million ($13,356 million), as opposed to $1,013 million ($10,433 million) in Bodnaruk, Massa, and Simonov (2009).

Next, I compare the deal characteristics in interlocking and non-interlocking deals. As can be seen in Table 2.5, the deal characteristics are not substantially different among the sub-samples. Interlocking deals are slightly larger deals, while being more friendly: hostile deals, poison pills and proxy fights are not common among interlocking deals. Total fees and fees paid by the acquirer and target are larger in monetary terms, perhaps due to larger transaction values; but smaller in percentage terms. Also, interlocking deals are more likely to lead to post-bid competition. However, these differences are not statistically significant. The only significant difference among interlocking and non-interlocking deals is that toeholds mostly pertain to interlocking deals. This issue will be analyzed in detail in Section 2.7.2, where I show that results are robust to excluding the deals with toeholds from the sample.

At this point, an analysis of the firm characteristics in interlocking versus non-interlocking deals is in order. Basically, we would like to see if the targets significantly differ in some characteristics other than the interlocking relationship. If there are sig-

[15] Cai and Sevilir (2012) use a sample of *completed* M&As among public firms with the announcement date and effective date between 1996 and 2008. In their sample, the acquirer controls less than 50% of the target before the acquisition announcement and owns 100% of the target after the transaction whereas in my sample both of these threshold percentages are 50%. Cai and Sevilir (2012) find that among 1,664 deals, 65 have an "interlocking director" (a "first-degree connection", as they name it).

[16] Consistent with Bodnaruk, Massa, and Simonov (2009), I define toehold as a minimum of 5% ownership of the bidder in target's common stock as of the deal announcement.

Table 2.5: **Descriptive Statistics for Interlocking and Non-Interlocking Deals**

This table presents the deal characteristics for the subsamples of *interlocking* and *non-interlocking deals*. Variables are defined in Appendix 2. I report the mean and standard deviation. Unless stated differently, the number of observations (N) is 2,088.

	Interlocking Deals		Non-Interlocking Deals	
	Mean	Std. Dev.	Mean	Std. Dev.
Success Dummy	0.83		0.88	
All Cash Dummy, N=1974	0.32		0.29	
All Stock Dummy, N=1974	0.47		0.47	
Hostile Dummy	0.04		0.07	
Same Industry Dummy	0.46		0.58	
Same State Dummy	0.50		0.28	
Tech Deal Dummy	0.01		0.04	
Toehold Dummy	0.30		0.02	
Tender Offer Dummy	0.20		0.15	
Poison Pill Dummy	0.00		0.01	
Proxy Fight Dummy	0.00		0.00	
Merger Of Equals Dummy	0.04		0.02	
Pre-Bid Competition Dummy	0.03		0.04	
Post-Bid Competition Dummy	0.07		0.03	
Deal Value (M$)	2421.72	8933.33	1891.70	7386.03
Target Fees (M$), N=1329	5.95	9.46	5.60	8.21
Acquirer Fees (M$), N=719	5.74	9.24	4.36	7.12
Total Fees (M$), N=658	11.48	20.10	10.81	15.92
Target Fees (%), N=1329	0.76	0.68	0.88	0.95
Acquirer Fees (%), N=719	0.44	0.55	0.50	0.71
Total Fees (%), N=658	1.15	1.15	1.29	1.46

nificant differences among these groups, then we would suspect that some aspects other than the information transmission through the interlocking directors are behind the results of this paper. Table 2.6 reports the characteristics of interlocking targets and non-interlocking targets. The tests of differences reveal that these targets are not significantly different from each other in terms of financials, except that the interlocking targets are slightly larger in size and have smaller six months lagged returns.

Table 2.6: **Descriptive Statistics for Interlocking and Non-Interlocking Targets**

This table presents the descriptive statistics for targets in *interlocking* and *non-interlocking deals*. Variables are defined in Appendix 2. I report the mean, median and difference tests. The numbers in the test of difference columns denote p-values. Unless stated differently, the number of observations (N) is 2,088.

	Interlocking Deals (A)		Non-Interlocking Deals (B)		Test of Difference (A-B)	
	Mean	Median	Mean	Median	t-test	Wilcoxon z-test
Return on Equity	-0.17	0.05	-0.13	0.09	0.89	0.03**
Book to Market	0.89	0.63	0.66	0.54	0.31	0.71
Market Capitalization	1844.72	166.66	1247.02	171.06	0.01***	0.03*
Growth of Sales	0.13	0.10	0.18	0.11	0.40	0.76
Price to Earnings	3.23	7.59	12.44	13.35	0.40	0.02**
Debt to Equity	0.54	0.16	1.20	0.26	0.76	0.07*
Institutional Ownership	0.35	0.34	0.36	0.32	0.77	0.87
Volatility (daily, 6 months, %)	0.24	0.14	0.20	0.11	0.22	0.03**
Lagged Return	0.05	0.00	0.19	0.14	0.06*	0.00***
Std. Deviation (monthly, 2 years), N=1784	0.17	0.14	0.15	0.12	0.10	0.06*
Board Size	7.54	7.00	7.87	7.00	0.44	0.54
Busy Board Dummy	0.21		0.13		0.05**	
Degree Centrality	0.13	0.09	0.09	0.05	0.00***	0.00***
Avgerage Directorship	2.07	1.83	1.59	1.40	0.00***	0.00***
Interlock Count	8.21	6.00	4.98	3.00	0.00***	0.00***
G-Index, N=577	7.96	8.00	9.32	9.00	0.02**	0.02**
E-Index, N=577	1.78	2.00	2.36	2.00	0.03	0.02**
Classified Board Dummy, N=577	0.48		0.61		0.20	
High Entrenchment Dummy, N=577	0.26		0.45	0.00	0.07*	

In addition to target financials, Table 2.6 demonstrates board and corporate governance characteristics for interlocking and non-interlocking targets. Despite having similar board size, interlocking targets are more central in board networks than non-interlocking targets; with board centrality being proxied by variables commonly used in the literature: degree centrality, average directorship count and interlock count. This leads to a classification of 21% of the interlocking target boards as “busy boards”, as opposed to 13% of the non-interlocking target boards. Interlocking targets also have lower governance and entrenchment indices; only 26% of the interlocking targets are “highly-entrenched”, compared with 46% of the non-interlocking targets. Even though these differences are significant, in Section 2.7, I will demonstrate that the data does not support alternative explanations arising from network centrality or entrenchment literature.

Table 2.7 reports the acquirer characteristics for the sub-samples of interlocking and non-interlocking deals. Acquirers have significantly higher size and price to earnings ratios in interlocking deals, at the expense of smaller liquidity ratios. The tests of difference do not reveal any other significant differences.

Table 2.7: **Descriptive Statistics for Interlocking and Non-Interlocking Acquirers**

This table presents the descriptive statistics for acquirers in *interlocking* and *non-interlocking deals*. Variables are defined in Appendix 2. I report the mean, median and difference tests. The numbers in the test of difference columns denote p-values. The number of observations (N) is stated next to each variable.

	Interlocking Deals (A)		Non-Interlocking Deals (B)		Test of Difference (A-B)	
	Mean	Median	Mean	Median	t-test	Wilcoxon z-test
Return on Equity, N=1966	0.00	0.11	-0.38	0.14	0.86	0.06*
Book to Market, N=1950	0.72	0.49	0.46	0.39	0.44	0.09*
Market Capitalization, N=1950	16767.90	1157.65	13223.04	1814.44	0.00***	0.01**
Growth of Sales, N=1949	0.26	0.15	0.22	0.14	0.40	0.61
Price to Earnings, N=1949	70.09	13.38	18.80	17.28	0.08*	0.04**
Debt to Equity, N=1968	0.74	0.39	0.50	0.37	0.63	0.57
Net Market Leverage, N=1946	0.07	0.05	0.03	0.02	0.06*	0.08*
Cash over Net Assets, N=1972	0.22	0.08	0.34	0.06	0.29	0.45
Accounting Liquidity, N=1409	0.18	0.14	0.24	0.20	0.04**	0.03**

2.4 Interlocking Directors and the Probability of Becoming a Target

In this section, I examine whether having an interlocking director with the acquirer increases the probability of being selected among potential targets. In order to test this, first, I have to define a set of potential targets for each deal. Following Bodnaruk, Massa, and Simonov (2009), I start with the set of the firms that belong to the two-digit SIC code industry of the actual target and have similar size (within 30% band of the market capitalization of the actual target). I consider this set as my *basic sample*. I estimate a probit regression where the dependent variable is a dummy taking value 1 if there is a bid for the firm, and 0 otherwise.

Among the control variables are firm's return on equity; growth of sales; book to market, price to earnings, and debt to equity ratios; lagged return and volatility; institutional ownership and industry Herfindahl index.[17] Following the literature on geographic proximity, I also include a dummy variable in the regressions which takes value 1 if the target is in the same state as the acquirer, and 0 otherwise (Kang and Kim 2008).[18] I use either year and industry (two-digit SIC code) dummies, or deal dummies in the regressions. With the exception of dummies and indices, I winsorize all control variables at the bottom and top 1% to limit the effect of outliers.

The initial two columns of Table 2.8 reports the results of this probit regression. As can be seen, the interlocking dummy has a positive coefficient that is statistically significant at 1% level. This indicates that the main prediction of my model is empirically strongly supported: Interlocking firms are more likely to be selected as acquisition targets than non-interlocking firms. Moreover, the effect is economically substantial. Having an interlocking director with the acquirer raises the likelihood of becoming a target by 12.18% when industry and year effects are controlled for.

[17] Institutional ownership is the fraction of target's stock owned by institutional investors required to report 13F filings. The data is obtained from Thomson 13-F master files. The variables are defined in Appendix 2.

[18] Using a sample of partial block acquisitions, Kang and Kim (2008) show that acquirers have a strong preference for geographically proximate targets. Similarly, Almazan, de Motta, Titman, and Uysal (2010) find that firms located within industry clusters make more acquisitions.

Table 2.8: **Interlocking Directors and the Probability Of Becoming a Target**

This table presents the coefficient estimates of the probit regression where the dependent variable is a dummy taking value 1 if there is a bid for the firm, and 0 otherwise. For each announced deal, I create a set of potential targets who belong to the same two-digit (or three-digit) SIC code industry as the actual target and has similar size (market capitalization) or book to market (BM) or debt to equity ratio (DE); and run the regressions for this sample. The variable of interest is the *interlocking dummy*, which equals to 1 if the potential target has an interlocking director with the acquirer, and 0 otherwise. The control variables are target size; return on equity; growth of sales; book to market, price to earnings, and debt to equity ratios; lagged return and volatility; institutional ownership; industry Herfindahl index; and a dummy taking value 1 if the target and the acquirer are located in the same state, and 0 otherwise. In each regression, either year and industry or deal dummies are included. Variables are defined in Appendix 2. The t-statistics in parentheses are estimated using standard errors adjusted for the industry clustering, with industry being defined as the two-digit SIC code. The symbols ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	2-Digit SIC Code 30% Size Band		3-Digit SIC Code 30% Size Band		2-Digit SIC Code 10% BM Band		2-Digit SIC Code 10% DE Band	
Interlocking Dummy	0.948***	1.102***	0.874***	1.078***	1.056***	1.239***	0.896***	1.084***
	(10.51)	(8.71)	(7.19)	(6.00)	(12.11)	(10.62)	(7.10)	(6.12)
Return on Equity	–0.007	–0.006	0.002	–0.019	–0.073***	–0.065**	–0.088***	–0.044
	(–0.34)	(–0.25)	(0.07)	(–0.91)	(–3.25)	(–2.36)	(–3.54)	(–0.94)
Log Book to Market	0.040**	0.012	0.083***	0.047*			0.095***	0.070***
	(2.45)	(0.55)	(3.51)	(1.89)			(4.56)	(3.90)
Log Market Cap.					–0.051***	–0.075***	–0.016*	–0.060***
					(–5.15)	(–7.83)	(–1.81)	(–5.44)
Growth of Sales	–0.066***	1.633***	–0.104***	–2.114***	0.016	1.280***	–0.036	3.904***
	(–4.53)	(12.45)	(–3.20)	(–5.89)	(0.67)	(7.01)	(–1.23)	(22.20)
Price to Earnings	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000
	(–0.73)	(–0.82)	(–0.95)	(–0.99)	(–0.05)	(–0.12)	(–1.14)	(–0.66)
Debt to Equity	0.005	0.003	0.036***	0.019*	0.001	–0.005		
	(0.69)	(0.31)	(2.85)	(1.83)	(0.08)	(–0.38)		

Table continues to next page.

	2-Digit SIC Code 30% Size Band		3-Digit SIC Code 30% Size Band		2-Digit SIC Code 10% BM Band		2-Digit SIC Code 10% DE Band	
Volatility	25.672***	12.873**	20.234***	12.936**	10.740**	1.091	–7.869*	–7.962
	(4.07)	(2.23)	(2.95)	(2.18)	(2.02)	(0.18)	(–1.86)	(–1.57)
Lagged Return	0.183***	0.208***	0.183***	0.222**	0.223***	0.269***	0.124**	0.180***
	(3.86)	(3.07)	(2.99)	(2.36)	(4.07)	(3.16)	(2.53)	(2.90)
Institutional Ownership	0.727***	0.901***	0.825***	1.067***	0.693***	0.827***	0.595***	0.750***
	(9.15)	(10.41)	(8.48)	(8.42)	(12.84)	(12.60)	(7.20)	(8.57)
Herfindahl Index	–0.337***	–0.544***	–0.092	–0.774***	–0.425***	–0.600***	–0.244	–0.647***
	(–3.85)	(–3.55)	(–1.11)	(–2.83)	(–3.71)	(–3.63)	(–1.21)	(–3.68)
Same State Dummy	0.784***	1.010***	0.826***	1.179***	0.812***	1.024***	0.618***	0.983***
	(4.62)	(4.89)	(4.05)	(4.46)	(5.04)	(5.47)	(3.25)	(4.01)
Intercept	–0.980***	–1.980***	–0.816***	–2.155***	–0.366***	–1.654***	–0.673***	–0.979***
	(–15.68)	(–29.18)	(–9.08)	(–23.00)	(–4.88)	(–30.70)	(–8.91)	(–15.69)
Year Dummy	Yes	No	Yes	No	Yes	No	Yes	No
Industry Dummy	Yes	No	Yes	No	Yes	No	Yes	No
Deal Dummy	No	Yes	No	Yes	No	Yes	No	Yes
Pseudo R-sqr.	0.149	0.189	0.177	0.173	0.158	0.201	0.157	0.290
Num. of obs.	60072	60072	32943	32920	57829	57829	57252	57252

As potential target is somewhat of a nebulous concept, I test my hypothesis for various specifications of the set of potential targets. As in Bodnaruk, Massa, and Simonov (2009), the first alternative I consider is changing the definition of industry to three-digit SIC code, while keeping the characteristic constant (30% band of market capitalization). Columns 3 and 4 of Table 2.8 reports the probit regression results for this sample. Notice that the results are very similar; there is only a small reduction in the coefficient value of the interlocking dummy. This is, perhaps, mostly due to a significant loss of observations since for this constrained set of three-digit SIC code industry, there are no other (nonselected) potential targets for some selected targets; eventually these are excluded from the regression.[19]

In the other alternative specifications, I keep the industry definition as two-digit SIC code, but I change the target financial used to define similarity. Following Bodnaruk, Massa, and Simonov (2009), I alternatively use a 10% band of book to market ratio to define similarity.[20] Columns 5 and 6 of Table 2.8 report the regression results for this sample. As a final alternative, I use a 10% band of debt to equity ratio, and report the results in columns 7 and 8 of Table 2.8. As can be seen in the table, the effect of interlocking directors is robust across various industry classifications and firm characteristics that are used to define the set of potential targets.

Throughout the study, I will analyze the results for all four specifications of the set of potential targets. Nevertheless, there are reasons to believe that *the most relevant specification is two-digit SIC code industry and 30% size band.* First, in 14% of the deals (287 deals from a total of 2,088), the target and the acquirer belong to the same two-digit SIC code, but not to the same three-digit SIC code industry. This means that one in every seven deals, two-digit rather than three-digit SIC code industry is decisive. Second, target size is one of the most decisive characteristics in target choice as it directly determines the amount of money the acquirer has to pay for target shares to complete the

[19]Due to the exclusion of the deals with only one potential (and selected) target, in the sample defined as three-digit SIC code and 30% band of market capitalization, only 59 deals are interlocking out of a total of 1806 deals.

[20]Actually, Bodnaruk, Massa, and Simonov (2009) mention a 15% band of book to market ratio as an alternative. I choose 10% band as this results in a sample that is closer to the basic sample with respect to the number of potential targets. Results are very similar if I use a band of 15% instead of 10%.

acquisition.[21] Finally, other studies base their results on potential targets defined using these characteristics (Bodnaruk, Massa, and Simonov 2009; Bouwman 2011; Hasbrouck 1985; Shivdasani 1993).

The ultimate lesson from the analysis in this section is that interlocking firms have higher probability of being selected among potential targets, with the effect being statistically significant at 1% level. This result is robust to various specifications of the potential set, which indicates that interlocking directors' effect is very strong. In the next Section, I relate this phenomenon to the target-side information asymmetry.

2.4.1 Targets with High Information Asymmetry

The idea that interlocking directors help overcome the information asymmetry problems by facilitating informational flows is a central feature of my model. Therefore, I expect to see stronger results after interacting the interlocking dummy with firm specific variables that proxy for the extent of information asymmetry in the target environment.

I rely on the prior literature to construct proxies for the information asymmetry level for a given firm.[22] The first variable I consider is a performance measure of the target firm, namely return on equity. Literature suggests that firms with good news are more likely to be publicly forthcoming with the news whereas firms with bad news are less likely to be so (Miller 2002; Verrechia 1983). Consequently, firms that are performing poorly would have higher information asymmetries as these firms would not be willing to reveal information. Hong, Lim, and Stein (2000) also note that "firm-specific information, especially negative information, diffuses only gradually across the investing public". Hence, we would expect a negative coefficient on the interaction term between the interlocking dummy and the performance of the target firm. As can be seen in Panel A of Table 2.9, conditioning on similar size, the interaction term has a negative coefficient, significant at the 5% (10%) level for the regression with deal (industry and

[21] Hasbrouck (1985) notes that "with credit rationing, potential bidders may face limitations on the absolute size of their outlay, and hence limitations on the size of the firm they may reasonably expect to acquire".

[22] My proxy selection closely follows Kang and Kim (2008).

Table 2.9: **Interlocking Directors and Targets with High Information Asymmetry**

This table presents the coefficient estimates of the probit regression where the dependent variable is a dummy taking value 1 if there is a bid for the firm, and 0 otherwise. For each announced deal, I create a set of potential targets who belong to the same two-digit (or three-digit) SIC code industry as the actual target and has similar size (market capitalization) or book to market (BM) or debt to equity ratio (DE); and run the regressions for this sample. In Panel A, the variable of interest is the interaction between the *interlocking dummy* and the *target's return on equity*. In Panel B, the variable of interest is the interaction between the *interlocking dummy* and the *small size dummy*, which equals to 1 if the target size is in the bottom 25% of the sample, and 0 otherwise. In Panel C, the variable of interest is the interaction between the *interlocking dummy* and the *standard deviation of the monthly target stock returns over the past two years*. Finally, in Panel D, the variable of interest is the interaction between the *interlocking dummy* and the *diversifying dummy*, which equals to 1 if the target and the acquirer belong to different industries (two-digit SIC code), and 0 otherwise. The control variables, whose coefficients are suppressed for brevity, are target size; return on equity; growth of sales; book to market, price to earnings, and debt to equity ratios; lagged return and volatility; institutional ownership; industry Herfindahl index; and same state dummy. In each regression, either year and industry or deal dummies are included. Variables are defined in Appendix 2. The t-statistics in parentheses are estimated using standard errors adjusted for the industry clustering, with industry being defined as the two-digit SIC code. The symbols ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	2-Digit SIC Code 30% Size Band		3-Digit SIC Code 30% Size Band		2-Digit SIC Code 10% BM Band		2-Digit SIC Code 10% DE Band	
	Panel A: Poorly Performing Targets							
Interlocking Dummy (a)	0.908***	1.045***	0.827***	1.013***	1.025***	1.205***	0.852***	1.035***
	(8.97)	(7.48)	(5.83)	(4.99)	(10.21)	(8.96)	(6.23)	(5.32)
Return on Equity (b)	–0.001	0.002	0.008	–0.012	–0.064***	–0.056**	–0.081***	–0.035
	(–0.03)	(0.08)	(0.30)	(–0.48)	(–2.99)	(–2.05)	(–2.98)	(–0.70)
(a) × (b)	–0.297*	–0.399**	–0.279*	–0.358**	–0.408*	–0.490	–0.358***	–0.430***
	(–1.84)	(–2.04)	(–1.71)	(–1.97)	(–1.69)	(–1.56)	(–2.89)	(–3.03)
Pseudo R-sqr.	0.149	0.189	0.177	0.174	0.158	0.202	0.158	0.291
Num. of obs.	60072	60072	32943	32920	57829	57829	57252	57252

Table continues to next page.

	2-Digit SIC Code 30% Size Band		3-Digit SIC Code 30% Size Band		2-Digit SIC Code 10% BM Band		2-Digit SIC Code 10% DE Band	
Panel B: Small Targets								
Interlocking Dummy (a)	0.922***	1.043***	0.860***	1.035***	1.019***	1.191***	0.864***	1.050***
	(8.33)	(7.18)	(5.75)	(4.91)	(10.86)	(9.41)	(5.96)	(5.26)
Small Size Dummy (c)	0.135***	–0.284***	0.127***	–0.259***	0.036	–0.009	–0.054	–0.011
	(3.50)	(–3.90)	(3.02)	(–3.50)	(1.06)	(–0.20)	(–1.44)	(–0.23)
(a) × (c)	0.297*	0.475**	0.284	0.429	0.135	0.051	0.196	–0.019
	(1.71)	(2.08)	(0.80)	(0.76)	(0.27)	(0.08)	(0.61)	(–0.04)
Pseudo R-sqr.	0.150	0.190	0.178	0.174	0.156	0.198	0.157	0.289
Num. of obs.	60072	60072	32943	32920	57829	57829	57252	57252
Panel C: Targets with High Standard Deviation of Monthly Returns								
Interlocking Dummy (a)	0.757***	0.774***	0.665**	0.667	1.172***	1.372***	0.934***	1.195***
	(3.60)	(2.86)	(2.00)	(1.55)	(5.65)	(5.27)	(3.71)	(3.36)
Standard Deviation (d)	0.191	0.046	–0.072	–0.074	0.070	–0.269	–0.397*	–0.167
	(0.81)	(0.19)	(–0.26)	(–0.27)	(0.31)	(–1.03)	(–1.84)	(–0.65)
(a) × (d)	0.998	1.913**	0.982	2.160*	–0.719	–0.882	–0.342	–0.438
	(1.28)	(1.98)	(0.92)	(1.67)	(–0.64)	(–0.69)	(–0.43)	(–0.41)
Pseudo R-sqr.	0.153	0.199	0.182	0.188	0.168	0.214	0.157	0.182
Num. of obs.	43415	43415	23648	23625	44685	44685	41228	41022
Panel D: Targets from an Industry Different to that of the Acquirer								
Interlocking Dummy (a)	0.782***	0.864***	0.745***	0.899***	0.893***	1.037***	0.708***	0.825***
	(4.63)	(3.92)	(3.60)	(3.21)	(7.66)	(6.57)	(3.99)	(3.86)
Diversifying Dummy (e)	0.062**		0.104***		0.068***		0.063**	
	(2.22)		(3.35)		(2.69)		(2.02)	
(a) × (e)	0.397	0.594*	0.371	0.571	0.393*	0.519*	0.504***	0.712***
	(1.51)	(1.75)	(1.00)	(1.21)	(1.79)	(1.70)	(2.71)	(3.25)
Pseudo R-sqr.	0.149	0.189	0.178	0.174	0.159	0.202	0.158	0.291
Num. of obs.	60072	60072	32943	32920	57829	57829	57252	57252
Year Dummy	Yes	No	Yes	No	Yes	No	Yes	No
Industry Dummy	Yes	No	Yes	No	Yes	No	Yes	No
Deal Dummy	No	Yes	No	Yes	No	Yes	No	Yes

year) controls. The results for the set of targets similar in debt ratio are even stronger, with significance at 1% level. In sum, coefficients for all specifications have the negative sign as expected, and except one (which has a p-value very close to 10%), are statistically significant. This is consistent with the idea that selection of the interlocking targets is driven by information asymmetry regarding target value, with asymmetry being proxied by poor performance. Notice that in order to be consistent with my control variables, I use return on equity as the performance measure. Results are even stronger if, as in Kang and Kim (2008), I use return on assets rather than return on equity as my proxy.

The second proxy I consider for the information asymmetry is the target size. Literature claims that small firms are subject to information asymmetry problems to a bigger extent than large firms are, due to the fact that information about small firms gets out more slowly than that about large firms. This is explained by investors' willingness to spend more resources on obtaining information regarding firms in which they can take large positions (Hong, Lim, and Stein 2000). Following Kang and Kim (2008), I include a dummy variable that takes value of 1 if the target size is in the bottom 25% of the sample, and 0 otherwise; and its interaction with the interlocking dummy in the regressions. As reported in Panel B of Table 2.9, the coefficient on the interaction term is positive and significant at the 5% (10%) level when I control for the deal (industry and year) effects. Hence, in our basic sample, interlocking targets are more likely to be selected than non-interlocking targets, particularly when they are small. The effect is not clear for other specifications of the potential target set, as there is too much dispersion in the size of the potential targets.

Next variable I consider as a proxy for information asymmetry is the standard deviation of past stock returns. Kang and Kim (2008) note that the higher the standard deviation, the greater the uncertainty about the target's prospects, and this leads to greater information asymmetry. They use standard deviation of the target monthly returns over the past five years prior to the deal announcement to control for the riskiness of the target. However, out of 76 selected interlocking targets, 35 are missing standard deviation for the prior five years. In order to have meaningful regressions, I adjust the definition of the proxy as the standard deviation of the monthly returns for two years prior to the deal announcement. We would expect to find a positive coefficient for the interaction term between standard deviation and interlocking dummy. Panel C of Table 2.9 shows that the interaction term is significantly positive at the 5% (10%) level when deal effects are controlled for, conditioning on firms with similar size and two-digit (three-digit) SIC code industry. Similar to the small size proxy, for other specifications, I cannot find significant coefficients perhaps due to the fact that most of the interlocking firms have this variable missing.

So far, I have focused on the information asymmetry in the target environment, which does not depend on the identity of the acquirer firm. However, what I am trying to capture is the information asymmetry between the target and the acquirer; hence, some characteristics of the acquirer may be relevant. The industries where the target and the acquirer operates are of special importance, as knowledge spill-overs are assumed to be present within industry groups. This argument suggests that the benefits of information obtained through the interlocking director will be greater when other information enhancement mechanisms, such as belonging to the same industry, are not available. I use the diversifying dummy, which is an indicator for the deals where the target and acquirer are from different two-digit SIC code industries, as a proxy for information asymmetry. Panel D of Table 2.9 illustrates that in all specifications, the interaction between diversifying dummy and interlocking dummy has a positive coefficient, as expected. The coefficient is statistically significant for five out of eight specifications, with the remaining three having p-values close to 10%. This is consistent with the idea that target-specific information is particularly important for diversifying deals where the acquirers are more likely to have informational disadvantages.

Overall, the results presented in this section are consistent with the hypothesis that interlocking directors help overcome the information asymmetry regarding the target value. The acquirers are more likely to select interlocking firms, particularly when they experience poor past performance, when they are small, when they are risky, or when they belong to a different industry. To the extent that these firms are those where target-specific information is more valuable, results indicate that interlocking directors have an important role in target selection.[23] In the next section, I relate the target selection phenomenon to the acquirer-side information asymmetry.

2.4.2 Acquirers with Financial Constraints

In this Section, I analyze whether financially constrained acquirers are more likely to select interlocking firms. The intuition behind is as follows. Debt reduces the ability to raise funds for acquisitions (Almazan, de Motta, Titman, and Uysal 2010). Acquirers with high debt ratios might be obliged to use their stock in transactions. In an effort to avoid undervaluation costs, these acquirers would be biased towards selecting interlocking firms so to be able to exploit their advantage in transmitting information on their value to the target. Therefore, I expect to see a stronger effect of the interlocking directors in target selection when the acquirer is financially constrained due to a high leverage ratio. On the contrary, since the acquirers abundant in cash holdings or liquid assets are not likely to face problems in fund raising, I expect a weakened effect of the interlocking directors in these cases.

Following the finance literature, I start by defining financially constrained firms as firms with high leverage. Specifically, I use the control variable in my study, debt to equity ratio, to proxy for firm's financial leverage. I include the interaction of this variable with the interlocking dummy in the regressions. Panel A of Table 2.10 demonstrates that the interaction term is positive in all specifications, and significant up to 1% level, except for the set of potential firms with same three-digit SIC code industry and similar size. Results indicate that acquirers are more likely to select interlocking firms, especially when they have high debt ratio. I obtain similar results when I use net market leverage defined in Almazan, de Motta, Titman, and Uysal (2010) instead of debt to equity ratio to proxy for financial constraints of the acquiring firm.

[23]Kang and Kim (2008) also use research and development (R&D) expenses of the target firm as a proxy. This variable would correspond to higher uncertainty regarding the target, hence higher information asymmetry. However, due to the fact that many actual targets are missing this variable, I cannot find any significant coefficient in its analysis. Out of 76 selected interlocking targets, 32 targets have missing values of R&D expenses.

Table 2.10: **Interlocking Directors and Acquirers with Financial Constraints**

This table presents the coefficient estimates of the probit regression where the dependent variable is a dummy taking value 1 if there is a bid for the firm, and 0 otherwise. For each announced deal, I create a set of potential targets who belong to the same two-digit (or three-digit) SIC code industry as the actual target and has similar size (market capitalization) or book to market (BM) or debt to equity ratio (DE); and run the regressions for this sample. In Panel A, the variable of interest is the interaction between the *interlocking dummy* and the *acquirer's debt to equity ratio*. In Panel B, the variable of interest is the interaction between the *interlocking dummy* and the *acquirer's cash over net assets*. Finally, in Panel C, the variable of interest is the interaction between the *interlocking dummy* and the *acquirer's accounting liquidity*. The control variables, whose coefficients are suppressed for brevity, are target size; return on equity; growth of sales; book to market, price to earnings, and debt to equity ratios; lagged return and volatility; institutional ownership; industry Herfindahl index; and same state dummy. In each regression, either year and industry or deal dummies are included. Variables are defined in Appendix 2. The t-statistics in parentheses are estimated using standard errors adjusted for the industry clustering, with industry being defined as the two-digit SIC code. The symbols ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	2-Digit SIC Code 30% Size Band		3-Digit SIC Code 30% Size Band		2-Digit SIC Code 10% BM Band		2-Digit SIC Code 10% DE Band	
Panel A: Acquirers with High Debt Ratio								
Interlocking Dummy (a)	0.859***	0.976***	0.776***	0.927***	0.901***	1.029***	0.724***	0.847***
	(9.20)	(7.75)	(5.29)	(4.40)	(11.11)	(10.02)	(4.91)	(4.74)
Acquirer Debt to Equity (b)	0.003***		0.007**		0.004**		0.024***	
	(3.77)		(2.40)		(2.07)		(3.54)	
(a) × (b)	0.191**	0.284*	0.242	0.411	0.355***	0.514***	0.520**	0.709**
	(2.12)	(1.94)	(1.02)	(1.08)	(2.95)	(2.93)	(2.31)	(2.34)
Pseudo R-sqr.	0.149	0.189	0.178	0.174	0.159	0.202	0.158	0.291
Num. of obs.	59886	59886	32803	32780	57713	57713	56754	56754

Table continues to next page.

	2-Digit SIC Code 30% Size Band		3-Digit SIC Code 30% Size Band		2-Digit SIC Code 10% BM Band		2-Digit SIC Code 10% DE Band	
Panel B: Cash Strapped Acquirers								
Interlocking Dummy (a)	1.104***	1.312***	1.109***	1.415***	1.207***	1.445***	1.180***	1.472***
	(11.40)	(10.05)	(8.47)	(7.19)	(10.44)	(10.00)	(12.04)	(9.33)
Acq. Cash over Net Assets (c)	–0.023*		–0.051***		–0.010		–0.080***	
	(–1.84)		(–2.84)		(–0.63)		(–4.32)	
(a) × (c)	–0.492**	–0.620***	–0.619***	–0.816***	–0.536***	–0.701***	–0.708***	–0.946***
	(–2.56)	(–2.88)	(–3.38)	(–3.59)	(–2.79)	(–3.15)	(–3.88)	(–4.17)
Pseudo R-sqr.	0.149	0.189	0.178	0.174	0.158	0.202	0.160	0.291
Num. of obs.	60072	60072	32943	32920	57829	57829	57252	57252
Panel C: Liquidity Constrained Acquirers								
Interlocking Dummy (a)	1.157***	1.413***	1.179***	1.573***	1.246***	1.443***	1.229***	1.550***
	(7.81)	(6.75)	(5.59)	(4.98)	(8.44)	(6.98)	(6.76)	(6.10)
Acq. Accounting Liquidity (d)	–0.049		–0.152***		0.012		–0.291***	
	(–0.86)		(–2.66)		(0.29)		(–3.57)	
(a) × (d)	–0.861**	–1.250**	–1.132**	–1.774***	–0.824*	–0.968*	–1.219***	–1.832***
	(–2.21)	(–2.47)	(–2.51)	(–2.77)	(–1.94)	(–1.71)	(–3.20)	(–3.17)
Pseudo R-sqr.	0.127	0.160	0.156	0.176	0.116	0.156	0.168	0.306
Num. of obs.	34844	34844	17337	17334	26731	26731	44454	44454
Year Dummy	Yes	No	Yes	No	Yes	No	Yes	No
Industry Dummy	Yes	No	Yes	No	Yes	No	Yes	No
Deal Dummy	No	Yes	No	Yes	No	Yes	No	Yes

Next, I analyze the effect of interlocking directors when acquirers have higher financial slack in terms of unused liquidity. Specifically, I interact the interlocking dummy with cash over net total assets as defined in Almazan, de Motta, Titman, and Uysal (2010). Panel B in Table 2.10 illustrates that, as expected, the interaction term has a negative coefficient which is economically and statistically significant at 1% across all specifications. Using accounting liquidity variable from the study of Bodnaruk, Massa, and Simonov (2009) rather than cash holdings provides very similar results. These are reported in Panel C of Table 2.10. The results reveal that acquirers which are constrained in liquidity display further bias towards selecting the interlocking firms.

Overall, the results presented in this section are consistent with the hypothesis that interlocking directors help overcome the information asymmetry regarding the acquirer value. The acquirers, particularly when they have high financial leverage, or when they are constrained in cash holdings or in liquidity, are more likely to select the interlocking firms. To the extent that these acquirers are those for whom it is more valuable to transmit acquirer-specific information to the targets, results indicate that interlocking directors play a significant role in target selection.

2.5 Interlocking Directors and Deal Structure

In this section, I analyze further the characteristics of interlocking deals. First, I show that interlocking deals economically benefit the acquirers, in the sense that they pay lower premiums for the target shares. Table 2.11 demonstrates this fact. Following the literature, first I define premium as the acquisition price, obtained from SDC, divided by the target price on 4 weeks prior to the announcement date. Panel A of table 2.11 shows that the mean (median) premium in interlocking deals is 37% (36%) as compared to 45% (57%) in non-interlocking deals. Nevertheless, the difference is not statistically significant. Next, I perform a regression analysis where, among the regressors, I include the variables that the literature has classified as the determinants of the premium paid by the acquirer. Panel B of Table 2.11 reveals that interlocking dummy has a negative coefficient, however, it is significant only at the 13% level when both year and industry dummies are included.

Table 2.11: **Interlocking Directors' Effect on the Premium Paid for Target Shares**

Panel A of this table presents the descriptive statistics for the premium paid by the acquirer for the target shares in interlocking and non-interlocking deals. I report the mean, median and difference tests. The numbers in the test of difference columns denote p-values. The number of observations is 1,777. Panel B of this table presents the coefficient estimates of the OLS and probit regressions where the dependent variable is one of the premium proxies. The control variables are target and acquirer size and book to market ratios; relative size; and all cash, hostile, same industry, same state, toehold, poison pill, tender offer, merger of equals, high tech, target termination fee, pre-bid and post-bid competition dummies. In each regression, either year or year and industry dummies are included. Variables are defined in Appendix 2. The t-statistics in parentheses are estimated using standard errors adjusted for the industry clustering, with industry being defined as the two-digit SIC code. The symbols ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

Panel A: Univariate Analysis

	Interlocking Deals (A)		Non-Interlocking Deals (B)		Test of Difference (A-B)	
	Mean	Median	Mean	Median	t-test	Wilcoxon z-test
Premium 4 Weeks	0.37	0.36	0.45	0.57	0.32	0.10
Premium High Price	0.38	0.48	0.64	0.49	0.00***	0.00***
Higher Price Dummy	0.26	0.00	0.36	1.00	0.00***	0.00***

Panel B: Regression Analysis

	Premium 4 Weeks		Premium High Price		Higher Price Dummy	
Interlocking Dummy	–0.043	–0.092	–0.144***	–0.114**	–0.593***	–0.535***
	(–0.92)	(–1.36)	(–2.79)	(–2.30)	(–3.76)	(–3.59)
Target Log Market Cap.	–0.031***	–0.017	–0.019*	–0.022*	0.026	0.025
	(–2.66)	(–1.29)	(–1.78)	(–1.79)	(0.70)	(0.54)
Acq. Log Market Cap.	–0.023*	–0.025**	0.036***	0.027***	0.057*	0.035
	(–1.79)	(–2.08)	(3.97)	(2.98)	(1.90)	(1.03)
Target Log Book to Market	0.038*	0.065***	0.047***	0.025	0.208***	0.161***
	(1.75)	(3.23)	(3.73)	(1.40)	(3.85)	(2.92)
Acq. Log Book to Market	–0.073***	–0.056***	0.041***	–0.005	0.089*	–0.018
	(–3.13)	(–3.07)	(3.05)	(–0.34)	(1.67)	(–0.33)

Table continues to next page.

	Premium 4 Weeks		Premium High Price		Higher Price Dummy	
Relative Size	–0.226***	–0.253***	–0.006	0.001	–0.202	–0.194
	(–3.75)	(–4.06)	(–0.19)	(0.03)	(–1.49)	(–1.41)
All Cash Dummy	0.042	–0.002	0.026	0.028	–0.028	0.026
	(0.84)	(–0.03)	(1.04)	(0.97)	(–0.27)	(0.27)
Hostile Dummy	0.134**	0.061	0.025	–0.013	0.154	0.118
	(2.60)	(0.69)	(0.52)	(–0.23)	(0.78)	(0.51)
Same Industry Dummy	0.002	0.042	0.012	0.010	0.069	0.038
	(0.05)	(1.00)	(0.46)	(0.39)	(0.81)	(0.55)
Same State Dummy	–0.027	0.016	0.039	0.021	0.177*	0.121
	(–0.63)	(0.47)	(1.32)	(0.96)	(1.71)	(1.48)
Toehold Dummy	0.004	0.050	–0.059	–0.028	0.042	0.127
	(0.02)	(0.22)	(–0.85)	(–0.40)	(0.22)	(0.61)
Poison Pill Dummy	–0.047	–0.054	–0.133	–0.044	–0.004	0.199
	(–0.34)	(–0.32)	(–1.28)	(–0.34)	(–0.01)	(0.36)
Tender Offer Dummy	0.005	0.021	–0.025	0.015	0.126	0.207**
	(0.10)	(0.47)	(–1.10)	(0.68)	(1.51)	(2.55)
Merger of Equals Dummy	–0.179***	–0.168**	–0.139**	–0.141**	–0.905***	–0.931***
	(–3.17)	(–2.57)	(–2.17)	(–2.55)	(–2.67)	(–2.74)
High Tech Dummy	0.041	–0.032	–0.189***	–0.092***	–0.689***	–0.387***
	(0.94)	(–0.95)	(–4.66)	(–2.70)	(–5.12)	(–3.33)
Target Term. Fee Dummy	0.028	–0.023	–0.010	0.041*	–0.067	0.107
	(0.62)	(–0.41)	(–0.43)	(1.74)	(–0.87)	(1.13)
Pre-Competition Dummy	–0.017	–0.088	0.098	0.111*	0.316	0.442*
	(–0.36)	(–1.06)	(1.59)	(1.82)	(1.32)	(1.96)
Post-Competition Dummy	–0.013	0.029	–0.060	–0.042	–0.351	–0.354
	(–0.17)	(0.32)	(–1.11)	(–0.73)	(–1.21)	(–1.15)
Intercept	0.700***	0.659***	–0.039	0.040	–0.055	0.950***
	(7.12)	(7.99)	(–0.41)	(0.49)	(–0.19)	(3.60)
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummy	No	Yes	No	Yes	No	Yes
Adj./ Pseudo R-sqr.	0.047	0.095	0.066	0.126	0.053	0.114
Num. of obs.	1569	1569	1569	1569	1569	1545

An alternative measure of premium is proposed in a recent work by Malcolm, Pan, and Wurgler (2009). This paper argues that the target's 52-week high price represents a reference point to investors and managers, and displays a strong effect on the determination of the acquisition price. The paper finds that acquisition prices are often biased towards this reference price. Following Malcolm, Pan, and Wurgler (2009), I define "high price" as the 52-week high stock price of the target firm over 52 weeks ending 4 weeks prior to the announcement date. As can be seen in Table 2.11, the premium calculated as the ratio of the acquisition price to "high price" is significantly lower in interlocking deals than in non-interlocking deals. I obtain similar results when I use a high price dummy to indicate the deals where acquisition price is higher than "high price", and use this as the dependent variable. Overall, the results suggest that interlocking deals are profitable for acquirers since they pay significantly lower premiums for target shares in these deals.

The acquirer's profitability in interlocking deals is also confirmed by Cai and Sevilir (2012). They demonstrate that acquirer shareholders obtain higher announcement returns in interlocking deals. They relate this to the acquirer's ability to pay lower takeover premiums and lower advisory fees in such deals. But what about the target shareholders? Given the lower level of premium paid for target shares, one would expect the target shareholders to be worse off in interlocking deals. Cai and Sevilir (2012) find that target shareholders obtain a mean five-day announcement return of 18.72% in interlocking deals as compared to 21.24% in non-interlocking deals, however, the difference is not significant. They state that "although target cumulative abnormal returns are lower in the presence of a first-degree connection [an interlocking director], target shareholders in such transactions still obtain sizeable returns at the acquisition announcement". Perhaps a more complete argument on this regard would be possible by analyzing also the target selection stage. Note that having an interlocking director with the acquirer significantly increases the likelihood of being selected by around 12%. This means that the insignificant reduction in the target abnormal returns might have been compensated with a significant increase in the probability of being selected, hence, obtaining the abnormal returns in the first place. Given this, one might argue that the presence of an interlocking director benefits the target shareholders, as well as the acquirer shareholders.[24]

Next, I analyze interlocking directors' effect on other relevant deal characteristics. Table 2.12 demonstrates that all stock payment is more likely in interlocking deals, with the effect being statistically significant. This is consistent with the hypothesis that interlocking directors help resolve information asymmetry problem regarding the acquirer value. Interlocking deals are also more likely to provoke competition, even though the effect is not significant. Finally, I find that the deal is less likely to be completed if there is an interlocking director, with the effect being insignificant.

Note that as interlocking deals are profitable deals for the acquirers, when an interlocking target is available, the choice of a non-interlocking target is highly suspicious. I analyze this issue in the next section.

2.6 Performance of Non-Selected Interlocking Firms

My model states that if the bidder privately receives a low signal on the valuation of the target, she will find it more profitable to make an offer to the unacquainted firm, as long as the synergy value is above some threshold level. This would correspond to a case where the actual target is a non-interlocking target, and is selected despite the fact that there is a very similar target interlocking with the acquirer. Hence, the model suggests that such non-selected interlocking targets are prone to bad performance. In this section, I test this hypothesis. Specifically, I analyze the accounting and stock market performance of the non-selected interlocking firms and provide evidence on their under-performance.

[24]Note that the M&A sample in Cai and Sevilir (2012) is slightly different to my sample regarding the time period, deal success and acquirer's ownership ratio in the target firm after the transaction. For this reason, the argument in this paragraph must be taken with precaution.

Table 2.12: **Interlocking Directors' Effect on All Stock Payment, Post-Bid Competition, and Deal Success**

This table presents the coefficient estimates of the probit regressions where the dependent variables are all stock payment, post-bid competition, and deal success, respectively for each set of columns. The control variables are target and acquirer size and book to market ratios; relative size; and all cash, hostile, same industry, same state, toehold, poison pill, tender offer, merger of equals, high tech, target termination fee, pre-bid and post-bid competition dummies. In each regression, either year or year and industry dummies are included. Variables are defined in Appendix 2. The t-statistics in parentheses are estimated using standard errors adjusted for the industry clustering, with industry being defined as the two-digit SIC code. The symbols ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	All Stock Payment		Post-Bid Competition		Deal Success	
Interlocking Dummy	0.220	0.389**	0.243	0.268	–0.061	–0.006
	(1.21)	(2.14)	(1.18)	(1.16)	(–0.24)	(–0.02)
Target Log Market Cap.	0.031	0.079	0.167***	0.181***	–0.256***	–0.257***
	(0.70)	(1.60)	(3.05)	(3.01)	(–4.28)	(–4.10)
Acq. Log Market Cap.	–0.104*	–0.121**	–0.096*	–0.097*	0.284***	0.278***
	(–1.93)	(–2.28)	(–1.87)	(–1.69)	(5.29)	(5.06)
Target Log Book to Market	–0.166***	–0.153**	0.157	0.265*	0.042	0.015
	(–2.58)	(–2.33)	(1.25)	(1.86)	(0.44)	(0.17)
Acq. Log Book to Market	–0.344***	–0.329***	0.025	0.004	0.133*	0.070
	(–6.43)	(–5.89)	(0.23)	(0.04)	(1.68)	(1.00)
Relative Size	0.048	0.132*	0.069	0.164	–0.113	–0.088
	(0.70)	(1.88)	(0.81)	(1.41)	(–1.25)	(–0.91)
All Cash Dummy			0.410***	0.433***	–0.119	–0.060
			(3.12)	(2.66)	(–0.73)	(–0.33)
Hostile Dummy	–0.579***	–0.530***	0.903***	0.935***	–1.172***	–1.176***
	(–3.38)	(–2.86)	(5.18)	(5.02)	(–6.12)	(–6.07)
Same Industry Dummy	–0.032	–0.005	0.104	0.178	0.189*	0.279***
	(–0.39)	(–0.05)	(0.61)	(0.81)	(1.93)	(2.78)
Same State Dummy	0.108	0.005	0.025	0.181	0.127	0.035
	(1.16)	(0.04)	(0.17)	(1.10)	(1.52)	(0.37)
Toehold Dummy	–0.799***	–0.751***	–0.032	0.014	–0.274	–0.140
	(–3.83)	(–3.02)	(–0.14)	(0.05)	(–0.98)	(–0.46)
Poison Pill Dummy	–0.603*	–0.791***	–0.611	–0.820*	–0.019	–0.099
	(–1.95)	(–2.63)	(–1.53)	(–1.87)	(–0.06)	(–0.28)

Table continues to next page.

	All Stock Payment		Post-Bid Competition		Deal Success	
Tender Offer Dummy	–1.724***	–1.675***	–0.076	–0.069	0.260*	0.240
	(–12.42)	(–10.98)	(–0.46)	(–0.38)	(1.84)	(1.53)
Merger of Equals Dummy	0.757**	0.891**	0.487**	0.260	–0.125	–0.104
	(2.39)	(2.55)	(2.08)	(1.14)	(–0.66)	(–0.52)
High Tech Dummy	0.089	0.059	–0.287	–0.347	0.422***	0.539***
	(0.39)	(0.23)	(–0.83)	(–0.88)	(2.61)	(3.53)
Target Term. Fee Dummy	–0.240	–0.043	0.067	0.059	0.744***	0.971***
	(–1.63)	(–0.39)	(0.48)	(0.37)	(5.11)	(7.68)
Pre-Bid Competition Dummy	–0.232	–0.227	0.603***	0.396*	–0.440**	–0.578***
	(–0.99)	(–0.88)	(3.19)	(1.77)	(–2.13)	(–2.71)
Post-Bid Competition Dummy	–0.085	–0.078			–1.355***	–1.380***
	(–0.51)	(–0.42)			(–6.23)	(–5.84)
Intercept	0.690***	0.659**	–2.124***	–1.023***	0.736**	1.158***
	(3.38)	(2.43)	(–7.64)	(–2.83)	(2.56)	(3.17)
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummy	No	Yes	No	Yes	No	Yes
Pseudo R-sqr.	0.217	0.273	0.176	0.244	0.321	0.385
Num. of obs.	1823	1787	1726	1344	1823	1734

2.6.1 Accounting Performance

To analyze the post-announcement performance of the non-selected interlocking targets, I only consider the deals where a non-interlocking firm is selected as target whereas some interlocking potential target firms exist along with other non-interlocking potential targets. The interlocking dummy is defined as before, but in this specific sample. I follow Fahlenbrach, Low, and Stulz (2010) to perform a proper comparison of the performance of non-selected interlocking firms with that of their peers. I define change in performance of the firms as return on assets (ROA) averaged over the three years following the deal announcement divided by its average over the three years prior to the deal announcement. Table 2.13 demonstrates that mean and median change in performance of non-selected interlocking firms are negative across all specifications, with median (mean) being significantly different from zero in all (most) of them. Next, I define a control firm for each non-selected potential interlocking firm as another potential target firm in the same deal that is non-selected but non-interlocking, and that has the closest value of prior three year ROA to that of the non-selected interlocking firm. I adjust the change

Table 2.13: **Accounting Performance of Non-Selected Interlocking Firms with Respect to Their Peers**

This table analyzes the performance of the non-selected interlocking firms. The sample consists of deals where the selected target is non-interlocking whereas there are potential interlocking targets. I first define *change in ROA* of the firms as return on assets (ROA) averaged over the three years following the deal announcement (DA) divided by its average over the three years prior to the DA. Next, I define a control firm for each non-selected potential interlocking firm as another potential target firm in the same deal that is non-selected but non-interlocking, and that has the closest value of prior three year ROA to that of the non-selected interlocking firm. The variable of interest is the *adjusted change in ROA*, which is the change in ROA, adjusted by subtracting that of the control firm. Variables are defined in Appendix 2. I report the mean and median of the variables. The p-values in parenthesis are obtained from t-tests and signed rank tests which are used to determine whether the statistics are significantly different from zero. The symbols ***, **, and * denote statistical significance of variables at the 1%, 5%, and 10% levels, respectively.

	2-Digit SIC Code 30% Size Band		3-Digit SIC Code 30% Size Band		2-Digit SIC Code 10% BM Band		2-Digit SIC Code 10% DE Band	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Pre-DA Avg. ROA	-0.0876	0.1060***	-0.0100	0.0789**	0.0986***	0.1230***	0.0898***	0.1394***
	(0.57)	(0.00)	(0.86)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)
Post-DA Avg. ROA	0.0356	0.0719***	0.0019	0.0555*	0.0848***	0.1085***	0.0625***	0.0852***
	(0.11)	(0.00)	(0.96)	(0.07)	(0.00)	(0.00)	(0.00)	(0.00)
Change in ROA	-0.2695*	-0.3050***	-0.2961	-0.3611**	-0.1194	-0.0932***	-0.4217***	-0.3246***
	(0.08)	(0.00)	(0.22)	(0.02)	(0.24)	(0.01)	(0.00)	(0.00)
Adjusted Change in ROA	-0.4049*	-0.1630***	-1.1630	-0.3029**	-0.7042	-0.0422	0.0977	-0.0018
	(0.08)	(0.00)	(0.13)	(0.01)	(0.41)	(0.75)	(0.51)	(0.90)
Num. of obs.	111	111	64	64	91	91	58	58

in performance of the non-selected interlocking firm by subtracting that of the control firm. As can be seen in Table 2.13, in the basic sample, the non-selected interlocking firms have an average (median) of -40% (-16%) change in return on assets when change is adjusted using the peer firms, with significance at 10% (1%) level. The results are similar across the specifications, however the number of firms and significance of coefficients is not as high. This provides evidence on the idea that negative information regarding these interlocking firms must be the reason why they were not selected as targets.

2.6.2 Stock Market Performance

According to my model, the reason why an interlocking firm is not selected as the target is that the acquirer has received negative information on this potential target firm. If we expect the bad news on a firm to come out through time, we would be able to observe this as a deterioration in the stock market performance of the firm. As the bad news come out, the market would process the information and the stock price of the company would adjust. Therefore, we would expect a reduction in the stock price of such firms. In this section, I analyze whether the non-selected interlocking firms under-perform their peers in the stock market.

Following Bodnaruk, Massa, and Simonov (2009), I create portfolios of the potential targets and analyze their performance. As in the previous section, I only consider the deals where a non-interlocking firm is selected as target whereas some interlocking and non-interlocking potential target firms exist. I refer to such deals as "relevant deals", and analyze three different portfolios of potential target firms in these deals. As there will be an in-depth analysis, I consider only the basic sample where potential target firms are defined as firms that belong to the two-digit SIC code industry of the actual target and have similar size. I focus on the equal weighted returns in an attempt to reduce the noise inherent in defining potential targets.

The first portfolio I consider is the portfolio of interlocking firms that are not selected in relevant deals, which I name as the "interlocking portfolio". The second portfolio consists of all potential target firms in these deals that do not have an interlocking director with the acquirer, which I name as the "non-interlocking portfolio". The third portfolio is a sub-set of non-interlocking portfolio where, for each firm in the interlocking portfolio, a control firm that belongs to the same deal and has the closest lagged return value is selected from the non-interlocking portfolio. I name this portfolio as the "control portfolio". By construction, the number of firms added to the interlocking and control portfolios are same at each point in time, but the size of the portfolios may vary slightly as firms get delisted. Finally, for a comparison, I also consider CRSP equal weighted portfolio.

The details of the portfolio formation is as follows. Whenever a relevant deal is announced, the interlocking and non-interlocking potential target firms are added to the corresponding portfolios. Specifically, the firms are added to the portfolios on the day after the deal announcement and are held in the portfolio for 1 year (252 trading days). This is a dynamic portfolio where firms enter and exit at non-regular dates. Therefore, the number of firms in the portfolio varies with time depending on the announcement of relevant deals and the number of potential targets. As relevant deals occur often, the portfolios are non-empty from the creation date until the closing date. However, as the first relevant deal is announced on January 23, 1996 and the last on December 5, 2005, for few days in January and December, there are no firms in the portfolios. For these days, I assign the market portfolio returns to the portfolios. This results in a portfolio for the full period of January 1996-December 2006. I also consider 2 years and 3 years holding period portfolios which are for the periods of January 1996-December 2007 and January 1996-December 2008, respectively. Finally, I analyze the monthly return series that are obtained by compounding the daily returns of portfolios.

Figure 2.1 presents the cumulative returns of the equal weighted interlocking and non-interlocking portfolios for holding periods of one, two and three years. Note that all three portfolios outperform the CRSP equal weighted portfolio. In order to capture the risk, I regress each portfolio's returns (excess of risk free rate) on four factors: market, size, and book to market factors proposed by Fama and French (1993), and Carhart (1997) momentum factor.[25] In un-tabulated results, I find that these portfolios have

[25] I thank Kenneth French for providing the Fama and French (1993) factors on his website:

significant positive alphas. This is not surprising since the literature has already shed light on significant positive returns to the potential target firms.

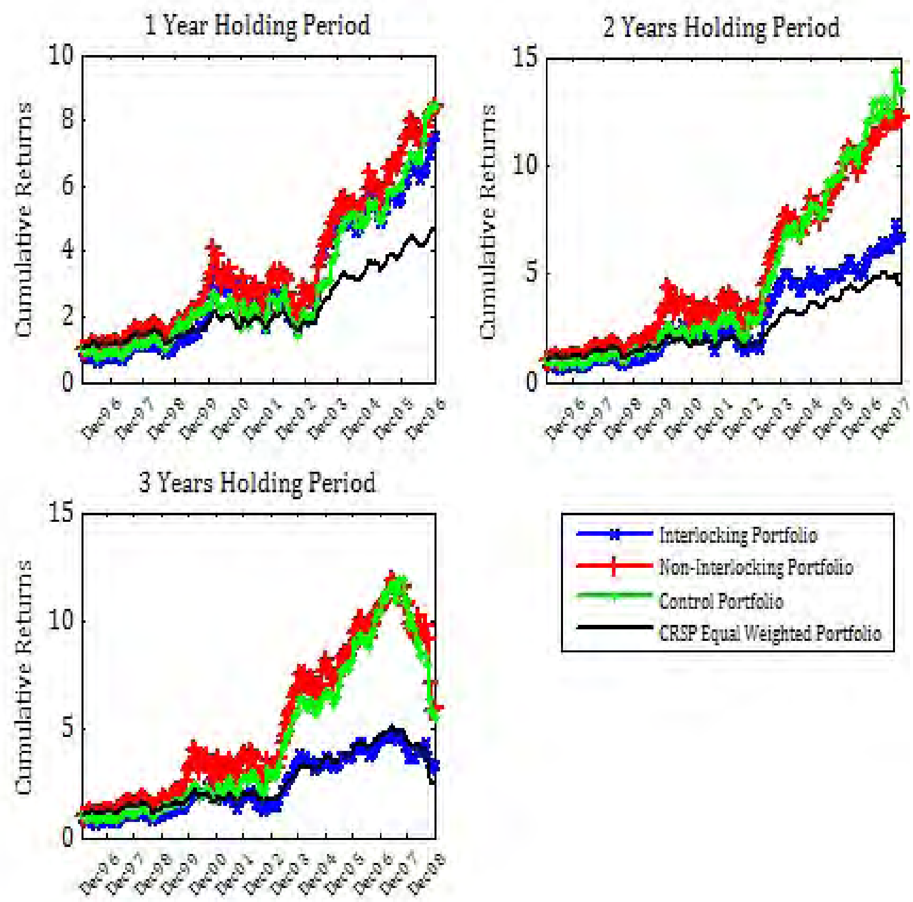

Figure 2.1: **Cumulative Returns of the Equal Weighted Interlocking and Non-Interlocking Portfolios.** This figure presents the cumulative returns of the interlocking and non-interlocking portfolios. The sample period starts in January 1996 and ends in December 2006, 2007, and 2008 for one, two and three years holding periods, respectively. Portfolio formation is described in the text.

Song and Walkling (2000) demonstrate the increase in firms' stock prices following the acquisition of their rivals and attribute this to the increased expectation that they will be taken over themselves, which is named as "acquisition probability hypothesis". Similarly, Cremers, Nair, and John (2009) show that anticipated takeovers affect the correlation of a stock's return with the market return. They construct a quintile-spread

http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/. I calculate the momentum returns using the procedures of Carhart (1997).

portfolio that buys firms with a high takeover vulnerability and sells firms with a low takeover vulnerability, and this portfolio has an annualized abnormal returns of 11.77% when four factors are controlled for. Finally, Edmans, Goldstein, and Jiang (2012) create a novel instrument to addresses the fact that prices are endogenous and increase in anticipation of a takeover, which they name the "anticipation effect".

Eckbo (1992) demonstrates that a significant portion of the rival firms across individual U.S. mergers earn non-zero abnormal performance as a result of the merger announcements. Despite their non-significant negative returns in non-horizontal deals, rivals in horizontal deals earn cumulative abnormal returns of a significant 1.26% within [-20,10] window of the announcement date. The abnormal returns are higher for the sample of U.S. horizontal challenged deals and when using the rival firms identified by the enforcement agencies. This effect is consistent with two scenarios: the market power hypothesis where the dominant coalition reduces industry output and increases the product price post-merger; and information signalling hypothesis where the merger signals opportunities for efficiency gains available to the non-merging industry rivals as well. However, consistent with the prior literature (Eckbo 1983, 1985; Schumann 1990), Eckbo (1992) finds evidence in favor of the information signalling hypothesis.

One could argue that interlocking and non-interlocking portfolio returns may be driven by the abnormal returns to the potential target (rival) firms. To assess the magnitude of the effect of acquisition announcements, I analyze the abnormal returns to non-selected potential target firms in relevant deals using standard event study methodology. Following Kang and Kim (2008), I first obtain the estimates of the market model for each firm by using 200 trading days of return data, beginning 220 days before and ending 21 days before the deal announcement. I use as the market return the CRSP equal weighted return, and sum the daily abnormal returns to get the cumulative abnormal return (CAR) from day t_1 before the announcement date to day t_2 after the announcement date. Table 2.14 reports the CARs for non-selected potential targets for different event windows [t_1,t_2]. For short event window of [-20,1], the cumulative returns

Table 2.14: **Cumulative Abnormal Returns for Non-Selected Interlocking and Non-Interlocking Firms**

This table presents the descriptive statistics for cumulative abnormal returns for potential target firms for different event windows [t_1,t_2]. I obtain the estimates of the market model for each firm by using 200 trading days of return data, beginning 220 days before and ending 21 days before the deal announcement. I use as the market return the CRSP equal weighted return, and sum the daily abnormal returns to get the cumulative abnormal return (CAR) from day t_1 before the announcement date to day t_2 after the announcement date. I report the mean, median and difference tests. The numbers in the test of difference columns denote p-values. The number of firms (N), out of which 170 are interlocking, is stated below each line.

	Interlocking Firms (A)		Non-Interlocking Firms (B)		Test of Difference (A-B)	
	Mean	Median	Mean	Median	t-test	Wilcoxon z-test
CAR[-20,1]	0.0059	0.0076	0.0001	-0.0013	0.73	0.49
N=5,619						
CAR[-1,1]	-0.0016	0.0021	-0.0001	-0.0022	0.82	0.47
N=5,619						
CAR[-5,5]	-0.0050	-0.0034	-0.0021	-0.0035	0.81	0.87
N=5,613						
CAR[-10,10]	-0.0163	-0.0211	-0.0015	-0.0032	0.38	0.40
N=5,603						
CAR[-20,20]	-0.0066	-0.0047	0.0000	0.0078	0.82	0.94
N=5,580						

are on average positive, however, for other windows they are negative.[26] What can be clearly seen from the table is that non-selected interlocking firms have lower cumulative abnormal returns than the non-selected non-interlocking firms. However, the differences are not significant.

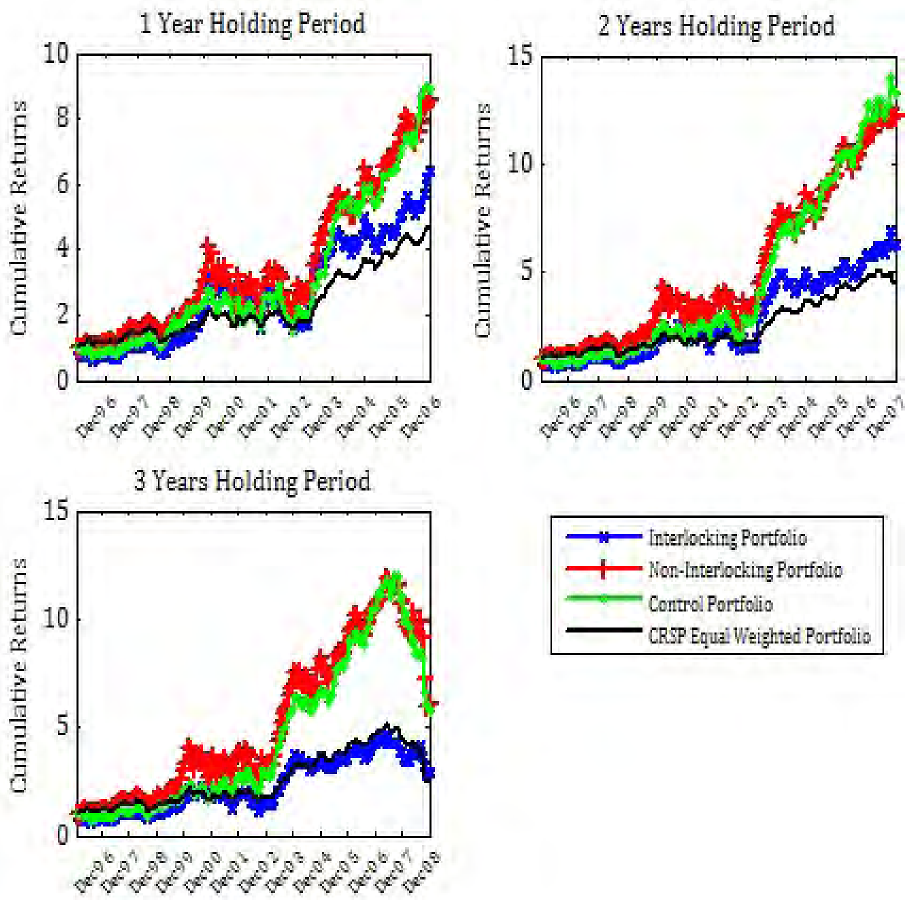

Figure 2.2: **Cumulative Returns of the Equal Weighted Interlocking and Non-Interlocking Portfolios - Starting from the Two Days after the Deal Announcement.** This figure presents the cumulative returns of the interlocking and non-interlocking portfolios. The sample period starts in January 1996 and ends in December 2006, 2007, and 2008 for one, two and three years holding periods, respectively. Portfolio formation is described in the text.

Next, I create portfolios starting from the second day after the deal announcement to clean out the large first day abnormal returns that may accrue to potential target firms. The reason is that I want to assess the long term stock market performance of

[26]Note that unlike Eckbo (1992), I do not distinguish between horizontal or non-horizontal deals.

firms following the deal announcements. The resulting portfolios are presented in Figure 2.2. As can be seen in the figure, now the cumulative returns of interlocking portfolios worsen compared to the non-interlocking portfolios. The difference is mostly reflected in one year holding period portfolios; two and three years holding period portfolios perform similar to those in Figure 2.1. For one year holding period, all three portfolios have similar performance that is superior to the CRSP market portfolio. However, as we increase the holding period, the interlocking portfolio starts to distinguish itself. Indeed, the three year holding period interlocking portfolio does not outperform CRSP portfolio, neither does two year holding period interlocking portfolio.

Finally, I regress each portfolio's excess returns on three Fama and French (1993) factors and Carhart (1997) momentum factor. The results of the regressions are presented in Table 3.8. As can be seen from the table, the portfolios have significant alphas, both economically and statistically. Note that the alphas I obtain from the portfolios of potential target firms is consistent with what Cremers, Nair, and John (2009) obtain from the quintile-spread portfolio (an annualized 14-19% vs. 12%). However, whereas Cremers, Nair, and John (2009) determine firms from probit regressions run each year using all available firms, I focus on the firms that are similar to the actual targets during portfolio formation.

Let us analyze the alphas of portfolios with different holding periods. One year holding period portfolios of potential target firms have significantly positive alphas, even when the first day abnormal returns are not considered. However, alpha of the interlocking portfolio is lower than that of the non-interlocking or control portfolio. What is more interesting is that, non-interlocking portfolio and control portfolio continue delivering significant alphas for two and three year holding periods whereas interlocking portfolio does not deliver alphas for long horizons. Figure 2.3 demonstrates in detail how the interlocking portfolio under-performs the non-interlocking portfolios and the CRSP equal weighted portfolio when the holding period is three years.

Table 2.15: **Regression Results for Portfolios of Non-Selected Interlocking and Non-Interlocking Firms**

This table reports OLS coefficient estimates when excess returns of the portfolios of non-selected potential target firms are regressed on four factors: market (MRKTRF), size (SMB), and book to market (HML) factors proposed by Fama and French (1993), and Carhart (1997) momentum factor (UMD). The sample period starts in January 1996 and ends in December 2006, 2007, and 2008 for one, two and three years holding periods, respectively. Portfolio formation is described in the text. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

Portfolios	Intercept	t-stat	MRKTRF	t-stat	SML	t-stat	HML	t-stat	UMD	t-stat	R-squared	N
One Year Holding Period												
Interlocking	0.0109*	(1.83)	1.1736***	(6.59)	0.9213***	(4.81)	-0.2563	(-1.17)	-0.4044***	(-3.99)	0.655	132
Non-Interlocking	0.0120***	(5.31)	1.0980***	(18.61)	0.9192***	(14.55)	-0.2491***	(-3.07)	-0.4257***	(-10.62)	0.933	132
Control	0.0143***	(3.00)	1.0915***	(8.77)	0.7902***	(6.48)	-0.1443	(-0.81)	-0.6279***	(-10.85)	0.764	132
Two Years Holding Period												
Interlocking	0.0073	(1.42)	1.3769***	(8.17)	0.9548***	(6.26)	0.0369	(0.22)	-0.3279***	(-3.11)	0.688	144
Non-Interlocking	0.0136***	(6.58)	1.0779***	(18.51)	0.9574***	(13.44)	-0.2298***	(-2.90)	-0.3796***	(-11.32)	0.927	144
Control	0.0146***	(3.60)	1.1160***	(11.41)	0.8732***	(8.09)	-0.0231	(-0.14)	-0.4974***	(-6.86)	0.763	144
Three Years Holding Period												
Interlocking	0.0065	(1.58)	1.0918***	(8.03)	0.7881***	(7.56)	-0.0651	(-0.46)	-0.3347***	(-5.62)	0.717	156
Non-Interlocking	0.0112***	(5.84)	1.0845***	(21.31)	0.9453***	(14.36)	-0.1467**	(-2.20)	-0.3706	(-9.14)	0.930	156
Control	0.0118***	(3.30)	0.9855***	(12.54)	0.7605***	(7.41)	-0.0496	(-0.42)	-0.4589***	(-6.82)	0.764	156

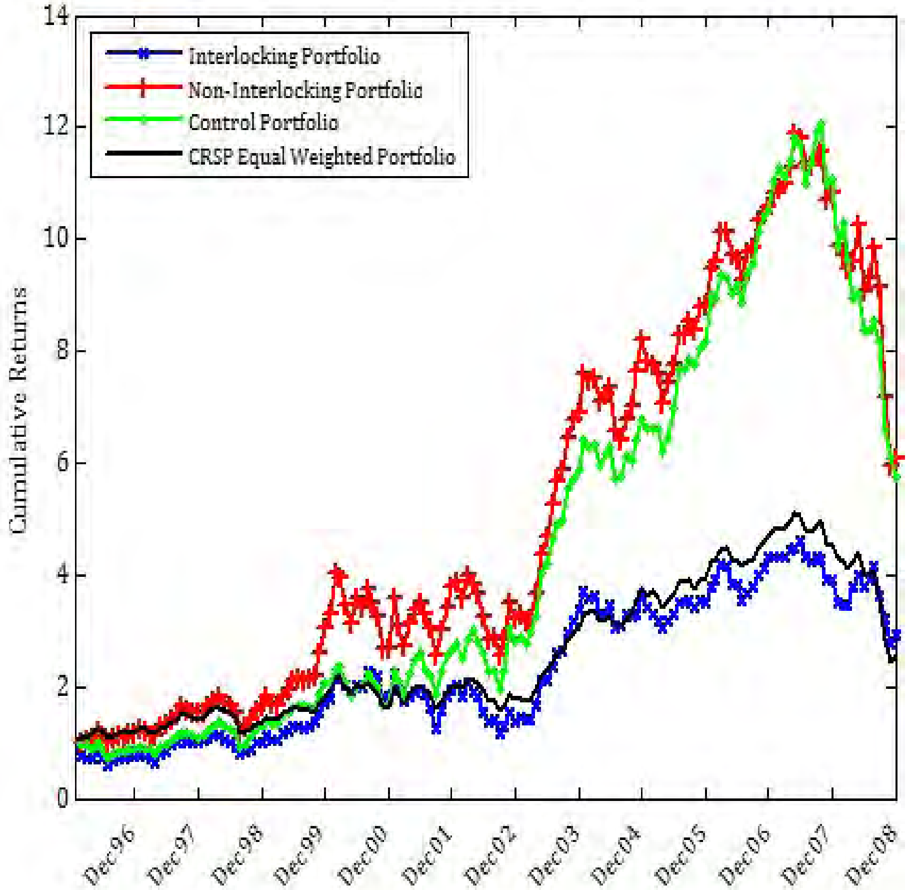

Figure 2.3: **Cumulative Returns of the Equal Weighted Portfolios with 3 Years Holding Period - Starting from the Two Days after the Deal Announcement.** This figure presents the cumulative returns of the interlocking and non-interlocking portfolios with three years holding period. The sample period is January 1996-December 2008. Portfolio formation is described in the text.

The findings in this section point to that *non-selected interlocking firms* underperform *non-selected non-interlocking firms* in the stock market, specifically when we consider portfolios of two or three years holding periods. This is consistent with the idea that bad news on the non-selected interlocking firms might have been the reason for the acquirer to select a non-interlocking firm in these deals. This is also consistent with alternative stories. For instance, it could be the case that non-selected interlocking firms do not have fundamental problems which would be considered as bad news, but simply that there are obstacles in acquiring them.[27] This would also result in under-

[27]It would be interesting to further analyze the characteristics of the firms in the interlocking portfolio,

performance of the interlocking portfolio given the acquisition probability hypothesis. However, even if this is the explanation behind the interlocking firms' returns, observing that the acquirers have not selected them in the first place provides evidence on that information flows from interlocking directors might have benefitted the acquirer in target selection.

2.7 Robustness Analysis

In this section, I analyze whether the results are driven by the endogeneity issues, sample selection or some alternative mechanisms. Basically, I analyze the possibility of reverse causality or omitted variables, the acquirer's ownership in the target prior to the deal, board centrality of the interlocking targets, and the entrenchment literature, as alternative explanations.

2.7.1 Testing the Endogeneity Concerns

The results in this paper support the model's first prediction: Having an interlocking director with the acquirer raises the likelihood of becoming a target, specifically when the potential problems that would arise from information asymmetry between the target and the acquirer are more relevant. This finding rejects the null hypothesis that target selection is independent of interlocking directors and, to the extent that appointment of interlocking directors are exogenous, supports the hypothesis that information flows through an interlocking director may induce a firm to become an acquisition target.

A potential concern is that creation of director interlocks may be endogenously determined. One concern is the reverse causality. It may be the case that an acquirer that is interested in a specific target first initiates a board relationship with that target. To analyze this possibility, I manually collect information on the tenure of the interlocking directors from proxy statements available at SEC EDGAR database. I find that the

especially regarding the entrenchment issues.

mean (median) number of years that an interlocking directors spends on target firm before deal announcement is 6.4 (5) years and that on acquirer firm is 11.3 (9) years. If we consider the initial year of the interlocking relationship, i.e. the minimum of tenure at the target and that at the acquirer, the mean (median) is 4.9 (3) years.[28] To the extent that M&A transactions are not planned 3-4 years before the deal announcement, this finding suggests that reverse causality is not a plausible explanation for how interlocking directors relate to target selection.

A second concern is the role of the unobservables in target selection. An alternative explanation of the interlocking director effect is that interlocking firms have fundamentally different unobservable characteristics, and that these characteristics are related to the tendency of firms to pair in M&As. In other words, interlocking directors may be endogeneously determined. Literature provides theoretical background (Adams and Ferreira 2007; Harris and Raviv 2008; Hermalin and Weisbach 1998) and empirical evidence (Coles, Daniel, and Naveen 2008; Linck, Netter, and Yang 2008) on that the board of directors are endogeneously determined according to the firm's corporate governance needs. Interlocking directors may be a result of this endogeneity.

A possible explanation for interlocking directors' effect on target selection is as follows. It could be the case that firms with greater similarity are more likely to select the same directors for their boards, resulting in the interlocking relationship. If the acquirers also tend to select targets with characteristics similar to theirs, observing an interlocking director between the M&A parties may be an artifact of acquirer-target similarity. Put in other words, omitted characteristics that relate to firm similarity may determine target selection and this may reveal itself in interlocking directors; suggesting that their information transmitter role is irrelevant for target choice. However, the approach taken in this study alleviates these concerns to a great extent. Note that in the regression analysis, for each deal, first I create a set of firms *similar* to the actual target (set of potential target firms), and then test target selection in this sample. If some specific characteristics of the actual target determine firm similarity that leads to an acquisition,

[28]These numbers are consistent with Cai and Sevilir (2012) who state that a typical interlocking director spends on average 6.4 years on both the acquirer's and the target's board before the deal announcement.

we would expect these characteristics to be present also in the potential targets. As long as such characteristics are controlled for in the definition of the set of potential targets, endogeneity should not be a concern.

Recall from Table 2.8 that the effect of the interlocking directors is economically and statistically very strong in all specifications where I control for industry, size, book to market and leverage of the firms by defining the potential target sets accordingly. Note that these characteristics overlap with the ones proposed in the literature as the determinants of becoming a takeover target (Cremers, Nair, and John 2009). To the extent that acquirer-target similarity is revealed in these variables, endogeneity should have been accounted for. In this section, I analyze further firm characteristics that may determine firm similarity. One potential omitted variable is the corporate governance of firms. The literature has found a set of variables that help explain firm corporate governance and I consider these as alternative characteristics to control for firm similarity (Coles, Daniel, and Naveen 2008; Linck, Netter, and Yang 2008). These are board characteristics, therefore any omitted variable resulting in the interlocking directors are expected to be present in these characteristics as well. To be more specific, in determining the potential targets, along with the two-digit SIC code industry, I use a 10% band of board size, or board independence (percentage of "outside directors" whose primary affiliations are with another firm), or degree centrality. Alternatively, I use a 10% band of ROA to control for the accounting performance of firms.

Results of this analysis is demonstrated in Table 2.16. The magnitude and significance of the positive effect of interlocking directors on target selection in these alternative specifications are very similar to those in Table 2.8. The controls introduced in this section do not diminish the effect of interlocking directors; the change is insignificant. These results suggest that interlocking directors are exogeneous to relevant firm characteristics up to a level such that controlling for them does not alter the results.

Table 2.16: **Testing the Endogeneity Concerns: Alternative Sets of Potential Targets**

This table presents the coefficient estimates of the probit regression where the dependent variable is a dummy taking value 1 if there is a bid for the firm, and 0 otherwise. For each announced deal, I create a set of potential targets who belong to the same two-digit SIC code industry as the actual target and has similar board size or board independence or degree centrality or return on assets; and run the regressions for this sample. The variable of interest is the *interlocking dummy*. The control variables are target size; return on equity; growth of sales; book to market, price to earnings, and debt to equity ratios; lagged return and volatility; institutional ownership; industry Herfindahl index; and same state dummy. In each regression, either year and industry or deal dummies are included. Variables are defined in Appendix 2. The t-statistics in parentheses are estimated using standard errors adjusted for the industry clustering, with industry being defined as the two-digit SIC code. The symbols ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	2-Digit SIC Code 10% Board Size Band		2-Digit SIC Code 10% Board Indep. Band		2-Digit SIC Code 10% Degree Cent. Band		2-Digit SIC Code 10% ROA Band	
Interlocking Dummy	0.977***	1.086***	0.922***	1.031***	1.083***	1.212***	0.874***	1.021***
	(11.12)	(8.96)	(11.77)	(11.07)	(10.42)	(8.83)	(5.95)	(5.42)
Return on Equity	–0.021	–0.034*	–0.018	–0.043***	–0.110***	–0.074***		
	(–1.10)	(–1.67)	(–1.15)	(–2.64)	(–4.47)	(–2.58)		
Log Book to Market	0.018	0.016	0.014	0.021	0.084***	0.036*	–0.016	–0.035
	(0.88)	(0.86)	(0.92)	(1.41)	(3.85)	(1.75)	(–0.47)	(–0.93)
Log Market Cap.	–0.044***	–0.060***	–0.055***	–0.058***	0.042**	–0.050***	–0.052***	–0.057***
	(–3.98)	(–5.79)	(–5.88)	(–6.82)	(1.97)	(–3.67)	(–3.41)	(–4.22)
Growth of Sales	–0.032**	2.077***	–0.016	–1.458***	–0.003	2.393***	0.056	1.328***
	(–1.98)	(15.79)	(–0.97)	(–13.06)	(–0.10)	(13.19)	(1.04)	(5.74)
Price to Earnings	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000
	(–1.14)	(–1.12)	(–1.01)	(–1.03)	(–0.85)	(–0.43)	(–0.62)	(–0.49)
Debt to Equity	–0.000	–0.004	–0.002	–0.008	0.004	–0.003	0.017	0.008
	(–0.03)	(–0.29)	(–0.16)	(–0.57)	(0.54)	(–0.21)	(1.58)	(0.62)

Table continues to next page.

	2-Digit SIC Code 10% Board Size Band		2-Digit SIC Code 10% Board Indep. Band		2-Digit SIC Code 10% Degree Cent. Band		2-Digit SIC Code 10% ROA Band	
Volatility	–3.275	–4.565	–3.203	–6.140	–1.339	–7.654	40.399***	12.155
	(–0.75)	(–0.88)	(–0.72)	(–1.39)	(–0.23)	(–1.41)	(3.25)	(0.86)
Lagged Return	0.157***	0.192***	0.158***	0.201***	0.204***	0.255***	0.334***	0.468***
	(3.50)	(3.30)	(3.84)	(3.53)	(3.38)	(3.44)	(4.56)	(4.22)
Institutional Ownership	0.616***	0.720***	0.574***	0.640***	0.661***	0.672***	0.652***	0.710***
	(10.36)	(10.48)	(11.38)	(10.76)	(11.55)	(9.59)	(11.92)	(10.81)
Herfindahl Index	–0.326***	–0.436***	–0.358***	–0.489***	–0.368***	–0.549***	–0.457***	–0.664***
	(–3.03)	(–3.41)	(–3.78)	(–3.78)	(–4.30)	(–3.69)	(–3.55)	(–3.31)
Same State Dummy	0.708***	0.906***	0.703***	0.864***	0.766***	0.970***	0.935***	1.160***
	(4.40)	(4.74)	(4.73)	(4.79)	(4.80)	(5.42)	(5.47)	(6.49)
Intercept	–0.700***	–1.864***	–1.079***	–2.050***	–1.017***	–1.797***	–0.455***	–1.725***
	(–14.59)	(–31.42)	(–18.56)	(–45.65)	(–7.99)	(–33.38)	(–4.52)	(–19.37)
Year Dummy	Yes	No	Yes	No	Yes	No	Yes	No
Industry Dummy	Yes	No	Yes	No	Yes	No	Yes	No
Deal Dummy	No	Yes	No	Yes	No	Yes	No	Yes
Pseudo R-sqr.	0.129	0.180	0.129	0.076	0.210	0.270	0.185	0.243
Num. of obs.	75493	75493	111267	111176	110701	110701	50196	50196

In a recent work, Bouwman (2011) finds that while firms attempt to select directors whose other directorships are at firms with similar governance practices, this matching of governance practices is imperfect because many other factors also affect the director choice. Moreover, directors acquainted with different practices at other firms influence the firm's governance to move toward the practices of those other firms. The result is the convergence of governance practices which is supportive of an effect running from interlocking directors to corporate governance changes.

A final piece of evidence on the extent of the exogeneity of the interlocking relationships comes from the previous literature. Koenig, Gogel, and Sonquist (1979) examine the reconstitution pattern (and its stability) of the interlocking relationships between the largest American firms which ended through the death of an outside director. They conclude that "interlocking directorates do not generally represent evidence of *close interconnections* between specific *corporations* but do connect some stable, city-based groups". The low reconstitution rate that they found for interlock ties (6%) is later confirmed in a similar study of Palmer (1993) where he considers reconstruction of interlock ties that were accidentally broken due to events such as death or retirement (8.9%).

Another variable that might relate to target selection is acquirer's ownership of target shares prior to the deal announcement, i.e. toehold. Toeholds may be a concern for both reverse causality and omitted variables, and I investigate this in the next section.

2.7.2 Testing the Alternative Sample

In Section 2.3.2, we have seen that toeholds are frequently observed in interlocking deals (30%), as opposed to their rare occurrence in non-interlocking deals (2%). Interestingly enough, the causal relationship between the toehold and the interlocking director is not clear. It may be the case that the interlocking directors induce minority acquisitions in the linked firms, or that owning a toehold leads to the assignment of the interlocking directors to the target board. To be able to distinguish one from another, a deeper historical analysis for these cases is required.

Toeholds may indicate an interest of the bidder (minority shareholder) in acquiring the target firm. One would expect that if a bidder is interested in acquiring a firm, buying its shares prior to the bid would give an advantage to the bidder. Hence, including deals with toeholds in the sample may bias the results in favor of target selection. However, empirically, we do not observe this behavior. Betton, Eckbo, and Thorburn (2009) note that toehold bidding has declined dramatically since the 1980s and is now rare. They report that "only 3% acquire toeholds during the six-month period leading up to the initial offer announcement, the period when the actual bid strategy is being formulated" (Betton, Eckbo, and Thorburn 2009). Moreover, the annual toehold frequency has been steadily declining since 1980s. They name this phenomenon as the "toehold puzzle". Given these facts, it is not likely that a strong bias would be present in the results of this paper.

Let us consider back the causality issue. For the moment, assume that the acquirer of the minority share in target firm assigns its directors to the target board, hence causality is from toehold to the interlocking director. Given the "toehold puzzle", two alternative explanations are left for why the acquirer in the first place would initiate an ownership to later assign an interlocking director: benefit from some degree of control over target firm actions or benefit from the inside information on the target firm.[29] The latter alternative is precisely what is analyzed in this paper. Therefore, I have opted to keep the deals with toeholds in my final sample.

Even though I have provided evidence on that including toeholds is an appropriate choice, to clear any suspicion on the results being driven by toehold considerations, I perform a very conservative robustness check. Specifically, I re-run each regression for a sample restricted to only deals without toeholds. This sample consists of 2,022 deals, of which, only 53 are interlocking. Given this low rate of interlocking deals (2.6%), it would not be surprising to observe a reduced significance of the coefficients. However, if we observe that overall significance of results diminishes substantially, even up to the point where the coefficient signs are altered, we might conclude that the results were driven by the deals with toeholds.

[29]It is most likely that both benefits are considered by the acquirer.

Table 2.17: **Testing the Alternative Sample: Excluding Deals with Toeholds**

This table presents the coefficient estimates of the probit regression where the dependent variable is a dummy taking value 1 if there is a bid for the firm, and 0 otherwise. For each announced deal, I create a set of potential targets who belong to the same two-digit SIC code industry as the actual target and has similar size (market capitalization). The variable of interest is the *interlocking dummy*, and its interaction with one of the information asymmetry proxies. The control variables are target return on equity; growth of sales; book to market, price to earnings, and debt to equity ratios; lagged return and volatility; institutional ownership; industry Herfindahl index; same state and deal dummies. Variables are defined in Appendix 2. The t-statistics in parentheses are estimated using standard errors adjusted for the industry clustering, with industry being defined as the two-digit SIC code. The symbols ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Interlocking Dummy (a)	0.838***	0.761***	0.786***	0.345	0.678***	0.743***	0.971***	1.019***
	(5.46)	(4.48)	(4.82)	(1.00)	(3.04)	(5.06)	(5.53)	(3.32)
Return on Equity (b)	0.000	0.009	0.002	0.007	–0.000	–0.001	–0.000	–0.016
	(0.01)	(0.32)	(0.10)	(0.23)	(–0.01)	(–0.02)	(–0.00)	(–0.71)
(a) × (b)		–0.481*						
		(–1.68)						
Small Size Dummy (c)			–0.278***					
			(–3.76)					
(a) × (c)			0.421					
			(1.58)					
Standard Deviation (d)				0.071				
				(0.26)				
(a) × (d)				2.370*				
				(1.73)				
(a) × Diversifying Dummy					0.414			
					(1.40)			
Log Book to Market	0.005	0.006	0.007	–0.027	0.005	0.004	0.005	–0.004
	(0.25)	(0.26)	(0.33)	(–1.06)	(0.26)	(0.20)	(0.25)	(–0.17)
Growth of Sales	1.361***	1.252***	1.328***	0.797***	1.584***	1.451***	1.475***	1.458***
	(9.08)	(6.39)	(8.73)	(2.67)	(8.31)	(8.67)	(8.44)	(5.52)

Table continues to next page.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(a) × Acquirer Debt to Equity						0.223		
						(1.61)		
(a) × Acq. Cash over Net Assets							–0.368*	
							(–1.91)	
(a) × Acq. Accounting Liquidity								–0.427
								(–0.63)
Price to Earnings	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000	–0.001*
	(–0.92)	(–0.92)	(–0.90)	(–0.43)	(–0.92)	(–0.92)	(–0.92)	(–1.76)
Debt to Equity	0.003	0.002	0.003	0.009	0.003	0.003	0.003	–0.006
	(0.25)	(0.19)	(0.29)	(0.80)	(0.22)	(0.26)	(0.27)	(–0.36)
Volatility	12.103**	12.301**	12.425**		12.058**	11.327*	12.289**	16.151***
	(2.06)	(2.09)	(2.12)		(2.05)	(1.92)	(2.09)	(2.72)
Lagged Return	0.204***	0.204***	0.205***	0.247***	0.204***	0.204***	0.205***	0.148***
	(3.00)	(3.01)	(3.01)	(3.50)	(3.00)	(3.00)	(3.00)	(3.69)
Institutional Ownership	0.916***	0.917***	0.911***	1.044***	0.917***	0.918***	0.917***	1.013***
	(10.29)	(10.32)	(10.28)	(9.16)	(10.29)	(10.68)	(10.27)	(9.50)
Herfindahl Index	–0.568***	–0.568***	–0.560***	–0.622***	–0.568***	–0.555***	–0.569***	–0.400***
	(–3.74)	(–3.72)	(–3.69)	(–3.95)	(–3.74)	(–3.61)	(–3.74)	(–4.32)
Same State Dummy	1.018***	1.019***	1.019***	1.111***	1.018***	1.022***	1.018***	0.697***
	(4.92)	(4.92)	(4.90)	(5.01)	(4.91)	(4.95)	(4.91)	(9.05)
Intercept	–1.946***	–1.928***	–1.937***	–1.977***	–1.984***	–1.965***	–1.966***	–2.056***
	(–26.96)	(–27.69)	(–26.70)	(–21.65)	(–27.65)	(–27.21)	(–26.32)	(–19.84)
Deal Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-sqr.	0.185	0.186	0.186	0.195	0.186	0.186	0.186	0.156
Num. of obs.	58745	58745	58745	42371	58745	58559	58745	33801

Table 2.17 reports the results of this robustness exercise. I find that basic sample results for the restricted sample (of deals without toeholds) are very similar to those for the unrestricted sample. As can be seen in column 1, the coefficient of interlocking dummy has only decreased to 0.838 from 1.102 even though 30% of the interlocking deals (toeholds) are excluded. The main hypothesis that interlocking firms are more likely to be selected as targets strongly holds in the restricted sample. The conclusions regarding target information asymmetry and acquirer financial constraints are neither contradicted. All coefficients of the interaction terms between the interlocking dummy and the proxies preserve their expected signs. The coefficients of interaction term with return on equity, standard deviation, and acquirer cash to assets ratio are still statistically significant. The coefficients of interaction term with small size, diversifying dummy, and acquirer debt to equity are not significant anymore, perhaps due to the loss in number of observations, but the p-values are slightly above 10% threshold. Only the interaction term with the acquirer liquidity has a coefficient with no significance, but one should note that many acquirer firms are missing this variable. Overall, this exercise demonstrates that results of the paper are not driven by toehold considerations.

2.7.3 Testing the Alternative Explanations

In this Section, I test whether the empirical phenomenon of bidders selecting interlocking targets, which my information asymmetry model predicts, is driven by some other considerations. The first alternative I consider is drawn from network centrality literature. A number of studies have shown that board networks affect strategic decisions such as the decision to acquire, the choice of target, and the method of payment. Stuart and Yim (2010) find that firms with central boards have a higher propensity to be targeted in private equity transactions. Similarly, **?** show that central boards are more likely to make an acquisition and to be acquired. Bouwman and Xuan (2010) also find that a firm is more likely to engage in mergers and acquisitions, among other financial activities, if it has interlocks with firms that engage in the same activity.

In addition to its effect on strategic decisions, board centrality also relates to firm performance. Firms centrally positioned in the boardroom network may have better access to information, and this may lead to better performance, both around mergers and in normal times. **?** find that firms with central boards of directors are associated with better performing acquisitions. Larcker, So, and Wang (2011) show that such firms earn superior risk-adjusted stock returns and future growth in return on assets. These studies indicate that board networks, created by multiple directorships, provide economic benefits. On the contrary, boards with multiple directorships may become ineffective monitors, which leads to weak corporate governance within the firm. Consistent with this consideration, Fich and Shivdasani (2006) find that firms with *busy boards*, those in which a majority of outside directors hold three or more directorships, are associated with weaker profitability and lower market to book ratios.

We have seen in Table 2.6 that interlocking targets are, in fact, significantly more central in the board network than non-interlocking targets, and more likely to have busy boards. Given the empirical findings in the literature and in this paper, it is possible that the interlocking targets are selected simply because their boards are more central, not because they have a direct link with the acquirer. The explanation could be as follows. Central firms are more likely to have busy directors, which perform their jobs ineffectively, and this results in under-performance of the firm (Fich and Shivdasani 2006). Firms with poor performance are more likely to be become hostile takeover targets, supporting the disciplinary role of corporate takeovers (Barber, Palmer, and Wallace 1995; Cremers, Nair, and John 2009; Hasbrouck 1985; Morck, Shleifer, and Vishny 1988).[30] Due to their centrality, we are also more likely to observe an interlocking director in these firms; this leads to the target selection phenomenon demonstrated in this paper. In order to rule out this explanation, I control for busy boards in the regressions.

[30]These studies have focused on the low market to book (q) ratios as a proxy for poor firm performance. The disciplinary role of corporate takeovers suggests that takeover targets represent cases where the corporation's internal controls and board level control mechanisms have been ineffective (Jensen 1986). Similarly, Shivdasani (1993) find that the outside directors of hostile targets have fewer incentives (as proxied by their lower equity ownership) to actively monitor managerial behavior, which is consistent with the view that board of directors and hostile takeovers are substitute mechanisms for corporate control.

Table 2.18: **Testing the Alternative Explanation: Network Centrality**

This table presents the coefficient estimates of the probit regression where the dependent variable is a dummy taking value 1 if there is a bid for the firm, and 0 otherwise. For each announced deal, I create a set of potential targets who belong to the same two-digit (or three-digit) SIC code industry as the actual target and has similar size (market capitalization) or book to market (BM) or debt to equity ratio (DE); and run the regressions for this sample. The variables of interest are the *interlocking dummy*, the *busy board dummy*, which equals to 1 if the majority of target board's outside directors hold three or more directorships, and 0 otherwise; and network centrality indices: *degree centrality*, *average directorship*, and *interlock count*. The control variables, whose coefficients are suppressed for brevity, are target size; return on equity; growth of sales; book to market, price to earnings, and debt to equity ratios; lagged return and volatility; institutional ownership; industry Herfindahl index; and same state dummy. In each regression, either year and industry or deal dummies are included. Variables are defined in Appendix 2. The t-statistics in parentheses are estimated using standard errors adjusted for the industry clustering, with industry being defined as the two-digit SIC code. The symbols ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	2-Digit SIC Code 30% Size Band		3-Digit SIC Code 30% Size Band		2-Digit SIC Code 10% BM Band		2-Digit SIC Code 10% DE Band	
Panel A: Controlling for Busy Boards								
Interlocking Dummy	0.947***	1.102***	0.873***	1.078***	1.059***	1.241***	0.898***	1.086***
	(10.55)	(8.73)	(7.19)	(6.01)	(12.33)	(10.74)	(7.11)	(6.15)
Busy Board Dummy	0.016	–0.005	0.018	0.003	–0.021	–0.014	–0.030	–0.027
	(0.76)	(–0.16)	(0.57)	(0.06)	(–0.60)	(–0.38)	(–0.80)	(–0.80)
Pseudo R-sqr.	0.149	0.189	0.177	0.174	0.158	0.201	0.157	0.290

Table continues to next page.

	2-Digit SIC Code 30% Size Band		3-Digit SIC Code 30% Size Band		2-Digit SIC Code 10% BM Band		2-Digit SIC Code 10% DE Band	
				Panel B: Controlling for Degree Centrality				
Interlocking Dummy	0.915***	1.085***	0.847***	1.061***	1.056***	1.240***	0.888***	1.077***
	(10.32)	(8.90)	(7.08)	(6.02)	(12.41)	(10.81)	(7.18)	(6.20)
Degree Centrality	0.602***	0.366**	0.605***	0.486**	0.000	–0.014	0.222	0.173
	(3.10)	(2.15)	(2.77)	(2.10)	(0.00)	(–0.09)	(1.20)	(0.91)
Pseudo R-sqr.	0.150	0.189	0.178	0.174	0.158	0.201	0.158	0.290
				Panel C: Controlling for Average Directorship				
Interlocking Dummy	0.930***	1.091***	0.860***	1.070***	1.055***	1.236***	0.893***	1.075***
	(10.61)	(8.89)	(7.23)	(6.04)	(12.19)	(10.66)	(7.22)	(6.17)
Average Directorship	0.051**	0.036	0.045*	0.038	0.003	0.014	0.014	0.032
	(2.16)	(1.40)	(1.90)	(1.31)	(0.15)	(0.49)	(0.51)	(1.02)
Pseudo R-sqr.	0.149	0.189	0.177	0.174	0.158	0.201	0.157	0.290
				Panel D: Controlling for Interlock Count				
Interlocking Dummy	0.917***	1.086***	0.848***	1.063***	1.054***	1.238***	0.888***	1.077***
	(10.37)	(8.89)	(7.06)	(5.99)	(12.31)	(10.74)	(7.17)	(6.17)
Interlock Count	0.010***	0.007**	0.011***	0.008**	0.001	0.001	0.004	0.003
	(3.02)	(2.11)	(2.84)	(2.27)	(0.37)	(0.20)	(1.25)	(0.93)
Pseudo R-sqr.	0.150	0.189	0.178	0.174	0.158	0.201	0.158	0.290
Year Dummy	Yes	No	Yes	No	Yes	No	Yes	No
Industry Dummy	Yes	No	Yes	No	Yes	No	Yes	No
Deal Dummy	No	Yes	No	Yes	No	Yes	No	Yes
Num. of obs.	60072	60072	32943	32920	57829	57829	57252	57252

Panel A of Table 2.18 report the regression results when, among the control variables, I include the busy board dummy, which takes value 1 if the majority of outside directors hold three or more directorships, and 0 otherwise. The coefficient of busy board dummy is not statistically significant in any of the specifications. In the basic sample with year and industry dummies, its coefficient is positive but not significant; and there is only a negligible reduction in the coefficient of the interlocking dummy, from 0.948 to 0.947. Overall, the results suggest that the economic and statistical significance of the interlocking relationship is robust to controlling for busy boards.

Next, I control for network centrality of the targets using the available proxies in the literature. The first measure I use is *degree centrality*, which measures a board's connectedness, and is defined as the number of interlocking outside boards. This measure is used in the studies of Stuart and Yim (2010) and Larcker, So, and Wang (2011). Following **?**, I normalize this variable by dividing it over the maximum degree centrality value of the corresponding year. The second measure I use is the *average directorship* of the target firm. The definition of this variable is obtained from Stuart and Yim (2010); it is the mean number of board seats held by the directors on each firm's board.[31] Finally, I include in my analysis the *interlock count*, which is the total number of interlocking directors with other firms as defined in Stuart and Yim (2010). Panels B, C and D of table 2.18 report the regression results when three proxies for network centrality are included, one at a time, as control variables. As can be seen, none of these variables significantly reduce the effect of the interlocking dummy. Clearly, the results in the paper are not driven by network centrality of the interlocking firms.

The second alternative I consider relates to the entrenchment literature. This literature has shown that cross-firm differences in corporate governance, specifically in anti-takeover defenses, have substantial effect on firm value and firm performance. Gompers, Ishii, and Metrick (2003) show that a governance index (the G-index) based on twenty-four provisions is negatively correlated with firm value. Bebchuk, Cohen, and Ferrell (2009) demonstrates that six of these provisions fully drive their results and propose the

[31]To be more precise, as in Stuart and Yim (2010), first I define *directorship count* as a count of the number of positions in distinct boards held by a director. Aggregating this to the firm level, *average directorship* is the mean number of directorship count held by the company directors.

entrenchment-index (the E-index) based on these. Bebchuk and Cohen (2005) find that an important component of both the G-index and the E-index is classified boards.

Corporate governance may also influence target selection. The interlocking directors might facilitate merger process not because of informational reasons, but because they act as negotiators so as to prevent anti-takeover defenses. D'Aveni and Kesner (1993) find that the deals in which the top managers of both the bidder and the target share elite connections (including directorships) are less likely to involve target resistance than the deals without such connections. If this is why interlocking directors are relevant for target selection, above all, we would expect that there are anti-takeover defenses present in these potential targets. However, Table 2.6 already provides evidence on that this is not the case. Indeed, if at all, the interlocking firms are less entrenched than the non-interlocking firms. Next, under this alternative explanation, we would expect to see a stronger effect of the interlocking directors for highly entrenched firms, with entrenchment defined as the degree of anti-takeover defenses in place. As in Masulis, Wang, and Xie (2007), I define a *high entrenchment* dummy, which takes value 1 if the firm has an E-index greater than 2, and 0 otherwise. I include an interaction variable between high entrenchment dummy and interlocking dummy in the regressions. If the purpose of interlocking directors is to overcome entrenchment issues, we would expect to see a significantly positive coefficient for this interaction term. On the contrary to the entrenchment explanation, in Panel A of Table 2.19, we see that the coefficient is insignificantly negative for all specifications.

Entrenchment theory also suggests that controlling for corporate governance variables would significantly affect the results. Panels B, C and D of Table 2.19 reports the results of the regressions when G-index, E-index, classified board indicator are used as controls, one at a time. Even though the economic impact of the interlocking dummy decreases to some extent, coefficients on the interlocking dummy is still positive and highly significant in all specifications. It is important to note that a great majority of the observations do not have corporate governance variables defined, so that the results of this section should be taken with caution. Nevertheless, analysis with this small sample reveals that entrenchment hypothesis is not a plausible candidate in explaining

Table 2.19: **Testing the Alternative Explanation: Entrenchment**

This table presents the coefficient estimates of the probit regression where the dependent variable is a dummy taking value 1 if there is a bid for the firm, and 0 otherwise. For each announced deal, I create a set of potential targets who belong to the same two-digit (or three-digit) SIC code industry as the actual target and has similar size (market capitalization) or book to market (BM) or debt to equity ratio (DE); and run the regressions for this sample. The variables of interest are the interaction between the *interlocking dummy* and the *high entrenchment dummy*, which equals to 1 if the target entrenchment index (a corporate governance index based on 6 provisions taken from Bebchuk, Cohen, and Ferrell (2009) is greater than or equal to 2, and 0 otherwise; and corporate governance indices: *governance index*, *entrenchment index*, and *classified board dummy*. The control variables, whose coefficients are suppressed for brevity, are target size; return on equity; growth of sales; book to market, price to earnings, and debt to equity ratios; lagged return and volatility; institutional ownership; industry Herfindahl index; and same state dummy. In each regression, either year and industry or deal dummies are included. Variables are defined in Appendix 2. The t-statistics in parentheses are estimated using standard errors adjusted for the industry clustering, with industry being defined as the two-digit SIC code. The symbols ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	2-Digit SIC Code 30% Size Band		3-Digit SIC Code 30% Size Band		2-Digit SIC Code 10% BM Band		2-Digit SIC Code 10% DE Band	
Panel A: Highly Entrenched Targets								
Interlocking Dummy (a)	0.714***	0.715***	0.687**	0.733**	1.205***	1.339***	0.661***	0.821***
	(3.57)	(2.88)	(2.56)	(2.33)	(5.54)	(4.29)	(3.47)	(3.14)
High Ent. Dummy (b)	0.041	0.057	0.000	–0.063	0.068	0.084	0.075	–0.001
	(0.61)	(0.78)	(0.01)	(–0.61)	(1.01)	(0.99)	(0.99)	(–0.01)
(a) × (b)	–0.415	–0.286	–0.393	–0.082	–0.776	–0.999	–0.400	–0.112
	(–0.78)	(–0.40)	(–0.51)	(–0.08)	(–1.57)	(–1.57)	(–0.78)	(–0.16)
Pseudo R-sqr.	0.115	0.171	0.125	0.214	0.155	0.202	0.166	0.266

Table continues to next page.

	2-Digit SIC Code 30% Size Band		3-Digit SIC Code 30% Size Band		2-Digit SIC Code 10% BM Band		2-Digit SIC Code 10% DE Band	
				Panel B: Controlling for Governance Index				
Interlocking Dummy	0.588***	0.629***	0.582**	0.717**	0.899***	0.932***	0.557***	0.787***
	(3.60)	(2.82)	(2.34)	(1.98)	(6.20)	(4.85)	(3.32)	(3.10)
Governance Index	0.019**	0.021*	0.025**	0.017	0.022**	0.030**	0.030*	0.022
	(1.97)	(1.69)	(1.99)	(0.94)	(2.21)	(2.36)	(1.96)	(1.27)
Pseudo R-sqr.	0.116	0.171	0.126	0.214	0.155	0.202	0.167	0.267
				Panel C: Controlling for Entrenchment Index				
Interlocking Dummy	0.593***	0.628***	0.584**	0.713*	0.908***	0.944***	0.556***	0.786***
	(3.63)	(2.80)	(2.33)	(1.96)	(6.34)	(5.00)	(3.42)	(3.13)
Entrenchment Index	0.045*	0.057**	0.043	0.026	0.052**	0.065**	0.068**	0.047
	(1.85)	(2.06)	(1.53)	(0.67)	(2.10)	(2.22)	(2.13)	(1.34)
Pseudo R-sqr.	0.116	0.172	0.126	0.213	0.155	0.202	0.168	0.267
				Panel D: Controlling for Classified Boards				
Interlocking Dummy	0.583***	0.622***	0.580**	0.715**	0.903***	0.941***	0.542***	0.785***
	(3.51)	(2.74)	(2.32)	(1.97)	(6.32)	(4.91)	(3.10)	(3.04)
Classified Board Dummy	0.028	0.077	0.060	0.066	0.054	0.053	–0.006	–0.076
	(0.44)	(1.19)	(0.72)	(0.68)	(0.90)	(0.74)	(–0.10)	(–1.00)
Pseudo R-sqr.	0.115	0.171	0.125	0.214	0.154	0.200	0.165	0.266
Year Dummy	Yes	No	Yes	No	Yes	No	Yes	No
Industry Dummy	Yes	No	Yes	No	Yes	No	Yes	No
Deal Dummy	No	Yes	No	Yes	No	Yes	No	Yes
Num. of obs.	4879	4879	2276	2276	4182	4182	3737	3737

the target selection phenomenon.

2.8 Concluding Remarks

This paper analyzes the role of interlocking directors in mergers and acquisitions within an information asymmetry context. According to the model I develop, acquirers are more likely to select the *acquainted targets* which, empirically, would correspond to firms that have an *interlocking director* with the acquirer. I find strong empirical support for model's implications. Conditioning on firms with similar industry and size characteristics, having an interlocking director with the acquirer raises the likelihood of becoming a target by 12 percent. I explain this by informational flows through interlocking directors, which help to overcome the information asymmetry between the target and the acquirer.

As a further evidence of the information asymmetry explanation, I find that acquirers are more likely to select the interlocking firms, particularly when these firms experience poor past performance, when they are small, when they are risky, or when they belong to a different industry. Moreover, acquirers that have high financial leverage, or insufficient cash holdings, or limited liquidity are further biased towards interlocking targets, and this is consistent with such acquirers' willingness to use stock as the payment method. To the extent that the above cases are those where target or acquirer-specific information is more valuable, results indicate that interlocking directors have a significant role in target selection. I also show that results are not driven by alternative explanations, such as network centrality or entrenchment.

My model not only explains the target selection phenomenon, but also predicts that an interlocking potential target that is not selected is prone to bad performance. I test the performance of non-selected interlocking firms and find supporting evidence. These firms have worse accounting and stock market performance as compared to their peers. In future research, the portfolio implications of the model's prediction on non-selected interlocking firms may be analyzed in further detail as some interesting results have already emerged. Also, the model can be extended to analyze the bidding behavior, negotiation process and method of payment; and the predictions can be tested using the data. Overall, the evidence presented in this paper suggests that interlocking directors mitigate inefficiencies that arise from informational advantages of the target or the acquirer in M&As, and this issue deserves further attention.

2.9 Appendix A: Proofs

Proof of Lemma 1:

Let us first remember bidder's posteriors on type of the acquainted target after observing the private signal:

$Prob(v_1 = v_H|\eta = h) = \frac{q\phi}{q\phi+(1-q)(1-\phi)} = \Phi_H$

$Prob(v_1 = v_L|\eta = h) = 1 - \Phi_H$

$Prob(v_1 = v_L|\eta = l) = \frac{(1-q)\phi}{(1-q)\phi+(q)(1-\phi)} = \Phi_L.$

$Prob(v_1 = v_H|\eta = l) = 1 - \Phi_L$

From this, it is easy to write the bidder's valuations of targets after receiving the signal:

$E[v_1|\eta = h] = \Phi_H v_H + (1 - \Phi_H)v_L$

$E[v_1|\eta = l] = \Phi_L v_L + (1 - \Phi_L)v_H$

$E[v_2] = qv_H + (1 - q)v_L = \overline{v}.$

Note that, since $\phi > 1/2$ (i.e., the signal is informative), we have that $E[v_1|\eta = h] > \overline{v} > E[v_1|\eta = l]$.

If the target is of type H, it will accept the offer if $p \geq v_H$. If the target is of type L, it will accept the offer if $p \geq v_L$. If bidder bids $p < v_L$, non potential target will accept the offer, hence there will be no transaction. Hence, we always restrict our attention to the cases where $p \geq v_L$. This generalizes to the bids for any target. Now let us focus our attention on the unacquainted target.

If bidder bids $v_L \leq p < v_H$ and the unacquainted target is of type L, the profits of the bidder will be: $\Pi = v_L + w - b$. Since this is decreasing in p, the bidder will offer the smallest possible p that the target will accept, which is $p = v_L$. Bidder's profits will be: $\Pi = w$. But if the target is of type H, it will reject the offer, so bidder's profits will be zero. Bidder's expected profits when $p = v_L$ is $E[\Pi] = (1 - q)(v_L + w - v_L) = (1 - q)w$.

If bidder bids $p \geq v_H$, again, as profits of the bidder is decreasing in p, the bidder will offer the smallest possible p that both targets will accept, which is $p = v_H$. Bidder's expected profits when $b = v_H$ is $E[\Pi] = E[v_2] + w - v_H = [qv_H + (1 - q)v_L] + w - v_H = w - [(1 - q)(v_H - v_L)]$.

Bidder will offer $p = v_H$ to the unacquainted target if $(1-q)w \leq w - [(1-q)(v_H - v_L)]$

$\Rightarrow w \geq [\frac{(1-q)}{q}(v_H - v_L)] \Rightarrow \frac{w}{v_H - v_L} \geq \frac{(1-q)}{q}$.

Otherwise, bidder will offer $p = v_L$ to the unacquainted target. Since $(1-q)w > 0$, the bidder will make an offer with certainty.

Proof of Lemma 2:

If the acquainted target is of type H, it will accept the offer if $p \geq v_H$. If the acquainted target is of type L, it will accept the offer if $p \geq v_L$.

a. High signal

Let's assume the bidder has received the signal $\eta = h$.

If bidder bids $v_L \leq p < v_H$ and the acquainted target is of type L, the profits of the bidder will be $\Pi = v_L + w - b$. Since this is decreasing in p, the bidder will offer the smallest possible p that the target will accept, which is $p = v_L$. Bidder's profits will be $\Pi = w$. But if the target is of type H, it will reject the offer, so bidder's profits will be zero. Bidder's expected profits when $p = v_L$ will be $E[\Pi|\eta = h] = Prob(v_L|\eta = h)(v_L + w - v_L) = (1 - \Phi_H)w$.

If bidder bids $p \geq v_H$, as profits of the bidder is decreasing in p, the bidder will offer the smallest possible p that both targets will accept, which is $p = v_H$. Bidder's expected profits when $p = v_H$ will be $E[\Pi|\eta = h] = E[v_1|\eta = h] + w - v_H = [\Phi_H v_H + (1 - \Phi_H)v_L] + w - v_H = w - [(1 - \Phi_H)(v_H - v_L)]$.

Bidder will offer $p = v_H$ to the acquainted target if $(1 - \Phi_H)w \leq w - [(1 - \Phi_H)(v_H - v_L)]$

$\Rightarrow w \geq [\frac{(1-\Phi_H)}{\Phi_H}(v_H - v_L)] \Rightarrow \frac{w}{v_H - v_L} \geq \frac{(1-\Phi_H)}{\Phi_H}$.

Otherwise, bidder will offer $p = v_L$ to the acquainted target. Since $(1 - \Phi_H)w > 0$, the bidder will make an offer with certainty.

b. Low signal

Let's assume the bidder has received the signal $\eta = h$.

If the bidder bids $v_L \leq p < v_H$ and the acquainted target is of type L, the profits of the bidder will be $\Pi = v_L + w - b$. Since this is decreasing in p, the bidder will offer the smallest possible p that the target will accept, which is $p = v_L$. Bidder's profits will be $\Pi = w$. But if the target is of type H, it will reject the offer, so bidder's profits will be zero. Bidder's expected profits when $b = v_L$ will be $E[\Pi|\eta = l] = Prob(v_L|\eta = l)(v_L + w - v_L) = \Phi_L w$.

If the bidder bids $p \geq v_H$, as profits of the bidder is decreasing in p, the bidder will offer the smallest possible p that both targets will accept, which is $p = v_H$. Bidder's expected profits when $p = v_H$ will be $E[\Pi|\eta = l] = E[v_1|\eta = l] + w - v_H = [\Phi_L v_L + (1 - \Phi_L)v_H] + w - v_H = w - [\Phi_L(v_H - v_L)]$.

Bidder will offer $p = v_H$ to the acquainted target if $\Phi_L w \leq w - [\Phi_L(v_H - v_L)]$

$\Rightarrow w \geq \frac{\Phi_L(v_H - v_L)}{1-\Phi_L} \Rightarrow \frac{w}{v_H - v_L} \geq \frac{\Phi_L}{1-\Phi_L}$.

Otherwise, bidder will offer $p = v_L$ to the acquainted target. Since $(\Phi_L)w > 0$, the bidder will make an offer with certainty.

Proof of Proposition 1:

Note that:

$Prob(v_H|\eta = h) = \Phi_H > q \Rightarrow \frac{1-\Phi_H}{\Phi_H} < \frac{1-\Phi_H}{q} < \frac{1-q}{q}$.

$Prob(v_L|\eta = l) = \Phi_L > (1 - q) \Rightarrow \frac{1-q}{q} < \frac{1-q}{1-\Phi_L} < \frac{\Phi_L}{1-\Phi_L}$.

Note also that $(1 - \Phi_H)w < (1 - q)w < (\Phi_L)w$. This implies:

Offering v_L to $T1|\eta = h \prec$ Offering v_L to $T2 \prec$ Offering v_L to $T1|\eta = l$.

Finally, $w - (\Phi_L)(v_H - v_L) < w - (1 - q)(v_H - v_L) < w - (1 - \Phi_H)(v_H - v_L)$. This implies:

Offering v_H to $T1|\eta = l \prec$ Offering v_H to $T2 \prec$ Offering v_H to $T1|\eta = h$.

However, the cutoffs $\frac{1-\Phi_H}{q}$ and $\frac{1-q}{1-\Phi_L}$ will be decisive. The below graph will help us making our conclusions.

$\frac{w}{v_H - v_L}$:	$\rightarrow \frac{1-\Phi_H}{\Phi_H}$	$\frac{1-\Phi_H}{\Phi_H} \rightarrow \frac{1-\Phi_H}{q}$	$\frac{1-\Phi_H}{q} \rightarrow \frac{1-q}{q}$	$\frac{1-q}{q} \rightarrow \frac{1-q}{1-\Phi_L}$	$\frac{1-q}{1-\Phi_L} \rightarrow \frac{\Phi_L}{1-\Phi_L}$	$\frac{\Phi_L}{1-\Phi_L} \rightarrow$
Offer to the unacq. target: Profits:	v_L $(1-q)w$	v_L $(1-q)w$	v_L $(1-q)w$	v_H $w-(1-q)\times$ $(v_H - v_L)$	v_H $w-(1-q)\times$ $(v_H - v_L)$	v_H $w-(1-q)\times$ $(v_H - v_L)$
Offer to the acq. tar.$\vert\eta = l$: Profits:	v_L $(\Phi_L)w$	v_L $(\Phi_L)w$	v_L $(\Phi_L)w$	v_L $(\Phi_L)w$	v_L $(\Phi_L)w$	v_H $w-(\Phi_L)\times$ $(v_H - v_L)$
Offer to the acq. tar.$\vert\eta = h$: Profits:	v_L $(1-\Phi_H)w$	v_H $w-(1-\Phi_H)\times$ $(v_H - v_L)$	v_H $w-(1-\Phi_H)\times$ $(v_H - v_L)$	v_H $w-(1-\Phi_H)\times$ $(v_H - v_L)$	v_H $w-(1-\Phi_H)\times$ $(v_H - v_L)$	v_H $w-(1-\Phi_H)\times$ $(v_H - v_L)$

Comparison of expected profits above gives us the bidder's optimum strategy conditional on each signal. Upon receiving a high signal, the bidder will offer $p = v_H$ to the acquainted target if $\frac{w}{v_H - v_L} \geq \frac{1-\Phi_H}{q}$. Otherwise, bidder will offer $p = v_L$ to the unacquainted target. Upon receiving a low signal, the bidder will offer $p = v_H$ to the unacquainted target if $\frac{w}{v_H - v_L} \geq \frac{1-q}{1-\Phi_L}$. Otherwise, bidder will offer $p = v_L$ to the acquainted target. This completes the proposition, and I provide a summary table below.

$\frac{w}{v_H - v_L}$:	$\rightarrow \frac{1-\Phi_H}{\Phi_H}$	$\frac{1-\Phi_H}{\Phi_H} \rightarrow \frac{1-\Phi_H}{q}$	$\frac{1-\Phi_H}{q} \rightarrow \frac{1-q}{q}$	$\frac{1-q}{q} \rightarrow \frac{1-q}{1-\Phi_L}$	$\frac{1-q}{1-\Phi_L} \rightarrow \frac{\Phi_L}{1-\Phi_L}$	$\frac{\Phi_L}{1-\Phi_L} \rightarrow$
Offer$\vert\eta = l$: Profits:	v_L to acq. tar. $(\Phi_L)w$	v_L to acq. tar. $(\Phi_L)w$	v_L to acq. tar. $(\Phi_L)w$	v_L to acq. tar. $(\Phi_L)w$	v_H to unacq. tar. $w - (1-q)\times$ $(v_H - v_L)$	v_H to unacq. tar. $w - (1-q)\times$ $(v_H - v_L)$
Offer$\vert\eta = h$: Profits:	v_L to unacq. tar. $(1-q)w$	v_L to unacq. tar. $(1-q)w$	v_H to acq. tar. $w - (1-\Phi_H)\times$ $(v_H - v_L)$	v_H to acq. tar. $w - (1-\Phi_H)\times$ $(v_H - v_L)$	v_H to acq. tar. $w - (1-\Phi_H)\times$ $(v_H - v_L)$	v_H to acq. tar. $w - (1-\Phi_H)\times$ $(v_H - v_L)$

2.10 Appendix B: Variable Definitions

Variable	Definition
Accounting Liquidity	The ratio of net liquid assets to total assets (Compustat items (4−5)/6)).
All Cash	Dummy variable equal to 1 if the deal is purely cash financed, and 0 otherwise.
All Stock	Dummy variable equal to 1 if the deal is purely stock financed, and 0 otherwise.
Average Directorship	The mean number of board seats held by the directors on the firm's board.
Board Size	The number of directors on the firm's board.
Board Independence	The percentage of *outside directors* on the firm's board.
Book Equity	*Stockholders equity* minus *preferred stock* plus *deferred taxes*.
Book to Market	The ratio of *book equity* to *market capitalization*.
Busy Board	Dummy variable equal to 1 if the majority of *outside directors* hold three or more directorships, and 0 otherwise.
Cash over Net Assets	The ratio of cash and marketable securities to *total assets* minus cash (Compustat items 1/(6−1)).
Classified Board	Dummy variable equal to 1 if the firm has a classified board, and 0 otherwise.
Debt to Equity	The ratio of debt (Compustat item 9) to *market capitalization*.
Deferred Taxes	Deferred taxes and investment tax credit (Compustat item 35), or, 0 if that is missing.
Degree Centrality	The number of interlocking outside boards, normalized by dividing over the maximum value for the corresponding year.
Diversifying	Dummy variable equal to 1 if the target and the bidder are from different industries, with industry being defined as the two-digit SIC code, and 0 otherwise.
E-index	Entrenchment index based on 6 provisions taken from Bebchuk, Cohen, and Ferrell (2009).
G-index	Governance index based on 24 provisions taken from Gompers, Ishii, and Metrick (2003).
Growth of Sales	The proportional change in sales over the fiscal year (ln(Compustat items 12/12(t−1))).
High Entrenchment	Dummy variable equal to 1 if the firm's E-index is greater than or equal to 2, and 0 otherwise.
High Premium	The ratio of the price paid for target shares recorded by SDC to the *high price*.
High Price	The 52-weeks high stock price of the target over 52 weeks ending 4 weeks prior to the announcement date.
Higher Price	Dummy variable equal to 1 if *high price* is higher than the price paid for target shares recorded by SDC, and 0 otherwise.
High Tech	Dummy variable equal to 1 if both the target and the bidder belong to a high tech industry as defined in Loughran and Ritter (2004), and 0 otherwise.
Hostile	Dummy variable equal to 1 if the deal is recorded by SDC as "hostile" or "unsolicited", and 0 otherwise.

Variable	Definition
Industry Herfindahl	Index variable that equals to sum of the squares of market shares (in sales) over all firms within the industry.
Interlock Count	The total number of interlocking directors with other firms.
Interlocking	Dummy variable equal to 1 if there exists at least one director that is common to both the target and the acquirer at the time of the deal announcement, and 0 otherwise.
Institutional Ownership	The fraction of firm stock owned by institutional investors required to report 13F filings.
Market Capitalization	The stock price multiplied by the number of shares outstanding at the end of the fiscal year (Compustat items 24×25).
Market Value	*Total assets* plus *market capitalization* minus *book equity*.
Merger of Equals	Dummy variable equal to 1 if the deal is structured as a merger of equals, and 0 otherwise.
Net Market Leverage	The ratio of debt minus cash and marketable securities (Compustat items $9-1$) to *market value*.
Outside Directors	The directors whose primary affiliations are with another firm.
Poison Pill	Dummy variable equal to 1 if a poison pill exists, and 0 otherwise.
Proxy Fight	Dummy variable equal to 1 if a proxy fight has taken place, and 0 otherwise.
Pre-Bid Competition	Dummy variable equal to 1 if another bid by a different bidder is recorded by SDC in the six months before the current bid, and 0 otherwise.
Post-Bid Competition	Dummy variable equal to 1 if another bid by a different bidder is recorded by SDC in the six months after the current bid, and 0 otherwise.
Preferred Stock	Liquidating value of preferred stock (Compustat item 10), or, if that is missing, the first available of the redemption value of preferred stock (Compustat item 56) or total preferred stock (Compustat item 130).
Premium	The ratio of the price paid for target shares recorded by SDC to the stock price of the target on 4 weeks prior to the announcement date.
Price to Earnings	The ratio of the year-end stock price to earnings per share (Compustat items 24/58).
Relative Size	The ratio of the *market value* of the target to the *market value* of the acquirer on 4 weeks prior to the announcement date.
Return on Assets	The ratio of operating income before depreciation to total assets of the prior fiscal year (Compustat items $13/6(t-1)$).
Return on Equity	The ratio of income before extraordinary items (adjusted for common stock equivalents) to average equity for the prior fiscal year (Compustat items $20/(60+60(t-1))/2$).
Same Industry	Dummy variable equal to 1 if the target belongs to the same industry as the bidder, with industry being defined as the two-digit SIC code, and 0 otherwise.

Variable	Definition
Same State	Dummy variable equal to 1 if the target is located in the same state (Compustat state variable, or if it is missing, SDC state variable) as the bidder, and 0 otherwise.
Stockholders Equity	Total stockholders equity (Compustat item 144), or, if that is missing, the first available of total common equity plus total preferred stock (Compustat items 60+130) or total assets minus total liabilities (Compustat items 6−181).
Success	Dummy variable equal to 1 if the deal is completed, and 0 otherwise.
Target Termination Fee	Dummy variable equal to 1 if target termination fee exists, and 0 otherwise.
Tender Offer	Dummy variable equal to 1 if the deal is tender offer, and 0 otherwise.
Toehold	Dummy variable equal to 1 if the fraction of the target's common stock owned by the bidder as of the deal announcement date is greater than 5%, and 0 otherwise.
Total Assets	The book value of assets (Compustat item 6).

Chapter 3

On the Economics of Hedge Fund Drawdown Status: Performance, Insurance Selling and Darwinian Selection

3.1 Introduction

The drawdown of an investment is a measure of the decline of the value of that investment from its historical peak. Drawdown analysis plays an important role in investment management, as the extent to which large drawdowns occur is an essential aspect of the evaluation of managers and their strategies. This is reflected in the widespread industry use of drawdown based performance evaluation measures, such as the Calmar and the Sterling ratios.[1] These measures are, ceteris paribus, negatively related to the maximum drawdowns that funds experience, which makes large drawdowns a negative

[1] The Calmar ratio is defined as the ratio of compound annualized rate of return to maximum drawdown, typically computed over a period of 3 years. The Sterling ratio is defined similarly but its denominator uses the average annual maximum drawdown plus 10%. In some variations, the risk-free rate is subtracted from the numerator, which results in a return-to-risk metric akin to the Sharpe ratio.

signal about the quality of the manager. In essence, large drawdowns proxy for risk and, consequently, play a negative role on performance evaluation. In this paper we look deeper into the economics behind drawdowns in the context of the hedge fund industry. We theoretically argue and empirically corroborate that drawdowns are related to future performance and that, in sharp contrast to the previous view, large drawdowns (plus fund survival) are predictive of outstanding performance. But these are just two of the many new insights into hedge funds that drawdown analysis delivers.

Our first departure from the traditional view consists of looking at a fund's drawdowns *relative* to the drawdowns of other funds in the market instead of in isolation. The second main departure is to analyze the *dynamics* of hedge funds drawdowns instead of its maximum past level. We argue that relative drawdowns and their dynamics are both predictive of the hedge fund's future performance. To develop these ideas, we define the *drawdown status* of a fund at a given moment in time as the decile to which the fund belongs in the drawdown distribution of the industry. Economic reasoning suggests that both the current level and the past evolution of this drawdown status are related to key aspects of hedge funds –such as the manager's talent and interests– and hedge fund investors' decisions –to exit or remain in the fund, to research more or less thoroughly, etc.– and are therefore predictive of future performance. This means that, *ex ante*, drawdown status is indeed a hedge fund *characteristic* related to performance. Our empirical analysis corroborates this hypothesis and also indicates that drawdown status is, from a quantitative standpoint, one of the most important performance-related hedge fund characteristics –despite being (incomprehensibly) neglected in the literature.

To illustrate the power of drawdown status as a key hedge fund characteristic related to performance, in Figure 3.1 we plot the cumulative returns of several comparable portfolios based on fund characteristics and performance measures. Panel A plots the cumulative returns of portfolios sorted by characteristics identified in the literature as being predictive of hedge fund performance: return, size, volatility and total delta;[2] Panel B plots the cumulative returns of portfolios sorted by performance evaluation measures

[2]See, for instance, Agarwal and Naik (2000, 2005), Brorsen and Harri (2004), Agarwal, Daniel and Naik (2009).

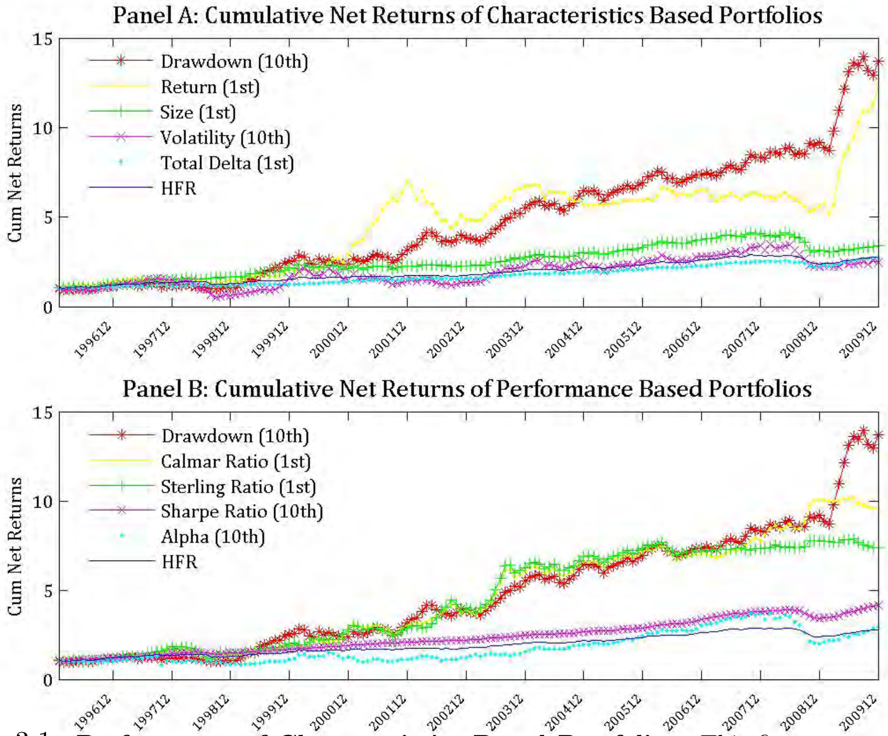

Figure 3.1: **Performance of Characteristics Based Portfolios.** This figure presents the cumulative net returns of the characteristics based portfolios. The sample period is January 1996-December 2009. The characteristics under analysis are drawdown, return, size, volatility, total delta, alpha, Sharpe, Calmar, and Sterling ratios. See Table 3.1 for the definition of characteristics. For each year, alpha is calculated as the sum of the 12 monthly alphas that is estimated from the fund-level time-series regression of excess returns on Fung and Hsieh (2004) seven factors, allowing for structural breaks, and includes both the regression intercept and the regression residuals. Sharpe ratio is average monthly excess returns divided by the standard deviation of the excess returns (excess of risk free rate) over the past three years. Calmar ratio is average annual return over past three years divided by maximum drawdown suffered over three years. Sterling ratio is average annual return over past three years divided by average annual maximum drawdown over three years and 10% is added to the denominator. At the end of each year t, we sort the characteristics of funds into ten deciles. We create two value weighted portfolios for each characteristic: the set of all hedge funds that are in the 1^{st} decile of years $t-1$, $t-2$, $t-3$ and the the set of all hedge funds that are in the 10^{th} decile of years $t-1$, $t-2$, $t-3$. We plot the one that performs best out of these two for each characteristic and label it. In brackets and next to the label of each strategy we indicate if the strategy holds the funds in the "1st" or "10th" decile.

widely accepted by academics or practitioners: alpha, Sharpe ratio, Calmar ratio and Sterling ratio. Each return series corresponds to a value weighted portfolio that each year holds the funds in the relevant extreme decile of the corresponding characteristic or performance measure in the previous three years. More specifically, we consider portfolios that each year hold all funds that belong to the intersection of the previous three years top versus bottom deciles. Figure 3.1 plots the one that performs best out of these two for each characteristic and performance measure analyzed. In brackets and next to the label of each strategy we indicate if the strategy holds the funds in the "1st" or "10th" decile. For instance, the line labeled 'Size (1st)', plots the cumulative return of a portfolio that each year (from 1996 to 2009) holds all hedge funds that belong to the intersection of the first size decile (smallest funds measured by assets under management, AUM) of the previous three consecutive years in the Hedge Fund Research (HFR) universe of hedge funds.[3] Notice that by reporting the 1st decile portfolio we are implicitly revealing that the portfolio of funds in the 10th decile performs worse than this one.

As we can observe in Panel A, the strategy labeled 'Drawdown' exhibits the best performance among all the characteristics based portfolios. The reader must acknowledge some surprise upon realizing that this portfolio holds every year all hedge funds in the intersection of the largest drawdown decile of the previous three years.[4] This result is indeed remarkable for at least three reasons. First, it indicates that drawdown status is a hedge fund characteristic that predicts outstanding performance. Second, in quantitative terms, drawdown status is a better predictor of hedge fund returns than other well-known characteristics. Third, outstanding performance is associated precisely with the funds that experienced large drawdowns in the past and are very far from their all time record when incorporated in the portfolio –in other words, funds that would tend to qualify as bad performers (and be viewed as managed by untalented traders) according to the standard drawdown based measures of performance. Another remarkable result inferred from Panel A is that total delta predicts future returns in the opposite direction as expected. In particular, we plot the portfolio of funds with the smallest total delta precisely because it outperforms the portfolio of funds with the largest total delta. This is in sharp contrast with the traditional view (Agarwal et al. (2009)) that performance

[3]For comparison we also include the cumulative return of the portfolio labeled 'HFR', which includes all funds in the HFR database.

[4]Panel A reports raw returns –that is, returns that are not risk-adjusted. We have computed risk-adjusted returns in the context of the Fung and Hsieh (2004) seven-factor model. We find that the largest alpha corresponds to the Drawdown portfolio. Thus, the superior performance of the drawdown based portfolio holds in terms of both raw and risk-adjusted returns. Finally, results are even more striking when we compare the performance of the 'Drawdown' strategy with the one associated to portfolios sorted on the basis of previous year status (as opposed to the previous three years status).

is positively related to incentives (total delta). This result is further analyzed later on.

Panel B reveals a very similar phenomena. Again, the best performance is associated to the Drawdown portfolio. Interesting enough, while alpha and Sharpe ratio operate in the expected way (best performance associated to the portfolio of funds in the 10th decile, that is, funds with the largest alpha and Sharpe ratio), the opposite occurs in the case of the Calmar and Sterling ratios: outstanding performance is associated to funds with the smallest ratios. Although this is conflictive with the use of these ratios as performance evaluation measures, it is consistent with the outstanding performance of the drawdown portfolio: low Sterling and Calmar ratios very likely are associated to funds that experienced large drawdowns in the recent past, that is, funds that most likely also belong to the Drawdown portfolio.

To summarize, the analysis of Figure 3.1 points at drawdown status as a legitimate candidate in the literature of hedge funds characteristics. It also shows the naiveté in the treatment of hedge funds' large negative returns (or volatility), in general, and drawdowns, in particular, both in the academia and according to industry standards (Calmar and Sterling ratios).

Why is drawdown status related to performance? The past drawdown status of a hedge fund is related to its future performance because it is informative of the manager's talent. A key distinctive feature of the hedge fund industry is a remuneration system for managers whereby success is extremely well compensated but in a very specific manner. The typical arrangement includes a fixed fee plus an incentive fee that is subject to a "high-water mark" clause. The fixed fee is applied to the AUM of the fund and ranges (across funds) from 0 to 6% with an average of 1.5%. The incentive fee ranges from 0 to 50% with an average of 19.1%.[5] Given these figures, it is obvious that the main goal for any manager is to collect incentive fees. However, the high-water mark clause allows the manager to collect incentives fees only from a particular investor when the net asset value (NAV) of the fund at the end of the measurement period is above its record during the measurement periods since the investor entered the fund. This is where the fund's

[5]These figures refer to the universe of hedge funds in the HFR data set, which is the one used in this paper. They are in line with those reported in other studies where alternative data sets are used.

drawdown history enters the picture: incentive fees are collected from both old and new investors in the fund when the fund is above the high-water mark –in other words, when its current drawdown is zero. Furthermore, funds currently at the high-water mark level are also expected to generate larger incentive fees in the near future because doing so will require only a strictly positive future return.[6] The opposite dynamics applies to funds currently facing a large drawdown: they do not collect incentive fees from old investors (those who entered the fund before the large drawdown occurred); and most likely they forgo fees from potential new investors who declined to enter the fund after observing the large drawdown. Moreover, managers should not expect incentive fees in the near future because that would require large returns that lift the fund's net asset value to the high-water mark. This means that, on the supply side, all managers seek to keep drawdown to a minimum. One way to achieve this, but perhaps not the only one, is talent in asset management. On the demand side, funds that currently experience large drawdowns are relatively cheap, in terms of incentive fees, for old investors: these do not pay them if they stay in the fund, but most likely will pay them if they leave and enter a new fund. Hence, it may be worthwhile to research them thoroughly and retain only those that are managed by talented traders. This process could result in the death of funds facing large drawdowns and managed by untalented traders. The last two points directly link drawdown status to talent in asset management. We contend that analyzing the *evolution* of drawdown status, which is just a measure of the relative position over time of each fund's drawdown with respect to the other hedge funds, allows one to discern talented managers. In essence, *drawdown status analysis* uses economic reasoning to predict the future performance of hedge funds by sorting out talented and untalented traders on the basis of past evolution of their drawdown status. The strategy 'Drawdown' plotted in Figure 3.1 is just one example of this new methodology's success.

In principle, talented managers –and especially those implementing a sound risk management technology– will tend to exhibit small drawdowns. Outstanding performance should therefore be associated with hedge funds that persistently exhibit a low drawdown status (in the 1st drawdown decile). However, in this paper we argue (and provide corroborating evidence) for this not being the case owing to the "contaminating"

[6] Or a return higher than hurdle rate, if it exists.

presence of funds that merely mimic low drawdown funds.[7] These are funds managed by untalented traders (i.e., those unable to deliver pure alpha returns) who specialize in strategies akin to selling insurance.[8] These strategies resemble a dynamic strategy of rolling over short positions in deep out-of-the-money put options on some broad stock or commodity index. All of them share the property of delivering positive returns in normal times but have the (hidden) cost of large losses in times of turmoil. By their very nature, these strategies usually place the fund in the lowest drawdown decile. They differ from the strategies of talented investors in that they are not associated with outstanding performance once proper account is taken of the true risks involved.

On the other hand, at any given time, the high drawdown decile is populated by both unlucky talented managers and untalented managers. In principle, we could expect this decile being associated to poor performance, as untalented managers will hit the decile more frequently. This reasoning is too simplistic as it ignores the death of funds. In this paper we argue and offer evidence consistent with a *Darwinian selection process* within the hedge fund industry: funds that "survive" in the largest drawdown decile for several periods are managed by talented managers and exhibit outstanding performance. Notice that these are funds that the traditional approach would consider very risky (after all, they suffered the largest drawdowns in the industry). They are, however, managed by talented managers, which means that high risk conditional on survival is tantamount to outstanding performance. This is one of our key insights and merits closer examination.

As mentioned previously, a distinctive feature of the hedge fund industry is an incentive structure that depends on the high-water mark clause. This means that old investors in a fund that suffers a large drawdown face a choice between staying in the fund (and saving a lot of fees, since incentive fees will not be paid until the fund returns to the high-water mark) and leaving to enter a new fund (where the investor starts at the high-water mark and must therefore expect to pay large fees). Clearly, the high-water mark clause plays in favor of staying in, but only when the fund's expected return remains positive –that is, when the manager is talented. Hence, it is at the time of

[7]We also document other factors contributing to this finding, such as the existence of systematic risk in hedge funds strategies and the backfilling bias.

[8]For instance, see Lo (2001), and Jorion (2007), for further details on these strategies.

such decisions that it is most worthwhile to gather extra relevant information about the manager's investment philosophy, strategy and reasons behind the large drawdown. But these are also times for managers to be less secretive and willingly disclose facets of their investment philosophy to rationalize the large drawdown. In fact, we should expect talented managers to be the ones more willing to reveal information. Hence, unlike normal times, rough times generate incentives for both extra researching (by investors) and disclosing (by managers). If this interaction operates efficiently, investors will leave the funds managed by untalented traders and stick to the talented ones. This process may result in a *Darwinian selection mechanism* whereby funds managed by untalented managers die fast. Under this hypothesis, these funds populate the high drawdown decile temporarily but are excluded from the set of funds that experience large drawdowns for a large enough number of periods. It is important to notice that while this latter set excludes all funds that die due to the Darwinian selection mechanism, it does not include all the "surviving" funds, but just those that survive in the highest drawdown decile –that is, it does not include the funds that move to lower drawdown deciles. In any case, it does include funds that survive for several periods beside remaining in the largest drawdown decile. According to our previous reasoning, this is only possible if investors are fully convinced that these funds are managed by talented traders.

At this point we should acknowledge that managerial self-confidence could also play a role in the survival of talented managers after a prolonged period of large drawdowns. First, some degree of self-confidence is required as incentive fees would only be collected if (large) positive returns materialize in the future and management fees are probably not enough to cover the fund's running costs. Second, we do not believe, however, that managerial *rational self-confidence* constitutes an alternative hypothesis to the *Darwinian selection* for the same phenomena, the survival of talented managers. The main reason is that if investors leave the fund, a rational self confident (talented) trader would find marginally optimal closing the fund and start a new one, as long as there is at least one potential investor to fool in the future.

In this paper we find portfolios of funds experiencing the largest drawdowns to have outstanding performance. Furthermore, this performance improves (monotonically in the number of years) when we restrict the portfolios to funds that survive in the highest drawdown decile for several years –which is consistent with the Darwinian selection hypothesis. We also provide additional evidence on the average number of consecutive periods that liquidated funds remain in the largest drawdown decile, on the evolution of flows into the funds and on the evolution of managerial ownership that further corroborate the existence of a Darwinian mechanism. The evidence indicates that these are not funds run by self-confident managers abandoned by external investors.

In our study we deviate from the standard methodology used in the hedge funds characteristics literature, which consists of regression analysis employing a predictive variable while controlling for previously identified characteristics related to performance. Instead, we use the *portfolio sort* methodology to assess the predictability of hedge funds returns. This approach is not new; in fact, it is the most widely used approach in the literature on asset pricing anomalies and has also been recently used in a hedge fund context in Jagannathan, Malakhov and Navikov (2010). Our basic construction consists of sorting portfolios on the basis of different lags in the drawdown status of hedge funds and then testing the performance of these portfolios in the context of the most widely accepted model in the hedge funds literature –namely the Fung and Hsieh (2004) seven-factor model.[9] The portfolio sorts methodology presents both advantages and disadvantages. On the positive side, it is versatile and allows for a rich set of variables to be tested. Also, and crucially, it enables direct assessment of outstanding performance in a risk-adjusted manner. Furthermore, as pointed in Jagannathan et al. (2010), the portfolio approach allows us to reduce measurement errors and to take into account the performance of funds at the sorting and portfolio formation stage as they remain in the analysis up to the time of their disappearance from the database. Finally, the methodology has the clear practical advantage of investors in general, and managers of funds of hedge funds in particular, exhibiting a genuine interest in its output. On the negative side, we highlight that unlike the case of stocks where the market portfolio exhibits no alpha, it turns out that the portfolio that includes all hedge funds in the

[9]In the Fung and Hsieh (2004) model, hedge fund excess returns are regressed on seven factors that have proven to have high explanatory power. These factors are the excess return on the S&P 500 index; the spread factors on size, term structure, and credit risk; and the excess returns on portfolios of lookback straddle options on currencies, commodities, and bonds.

HFR data set (henceforth, "the HFR portfolio") exhibits a strictly positive alpha.[10]

Both methodologies, however, suffer from an identification problem when analyzing the relationship between hedge fund characteristics and hedge fund performance. It is well known that the regression approach may yield faulty results when some relevant control variables are not properly accounted for. More specifically, outstanding performance may be attributed to a given characteristic just because what is actually a more dominating characteristic has not been identified and controlled for. Yet, the portfolio sort methodology may suffer form a similar problem. Simply put, a given sorting hedge fund characteristic may seem to explain outstanding performance, when in fact that performance is partially (or even completely) explained by some other characteristic. This problem can be addressed by imposing "conditional" sorts that control for the alternative characteristics, but data availability may impose a serious limitation on this approach. For all these reasons –and in order to dispel any suspicion that our results are driven solely by the use of portfolio sorting– in Section 3.8 we test our hypothesis in the context of the more traditional regression methodology and confirm that our results hold in this setting.

At this point we must argue in favor of drawdown status analysis even when identifying some hedge fund characteristic that partially explains the performance of some of our drawdown based portfolios (which, indeed, is not the case as we will see later on). This is better illustrated by means of an example. It is well known that hedge fund performance tends to deteriorate as funds receive large inflows and grow in size (Agarwal, Daniel and Naik (2006), Fung et al. (2008), Jagannathan et al. (2010)). This suggests that there is a "threshold" size for each hedge fund above which the manager is unable to keep up with outstanding performance. Now assume that we find that most of the outstanding performance of the large drawdown portfolios is related to size (small funds). In this case, the economic channel could be operating as follows. Some hedge funds managed by talented managers grow too much, above the threshold size. Then,

[10]While this is consistent with the existence of talent in the overall industry, it has been recently challenged in papers such as Fung, Naik and Ramadorai (2008) on account of the backfilling bias (the fact that funds only enter the HFR database after several years of good performance) and structural breaks in the return series. This last point is verified in Section 3.7 of this paper where we provide an analysis accounting for structural breaks.

some factors that affect performance, such as operational risk, starts negatively affecting the fund. At some point the fund suffers a large drawdown that places it in the largest drawdown decile, what generates large capital outflows. Now that the fund size is below the threshold size, it is expected to deliver outstanding performance in the future again (as it still is managed by a talented trader). Aware of this, many old investors in the fund do not let the fund go (Darwinian selection) and stick to it through several periods of large drawdown status. This story is perfectly consistent with our analysis and indeed highlights the importance of drawdown status analysis to predict performance. The story just points at a specific channel (fund size) for which drawdown status analysis works.

Our results are of interest on their own right but also when balanced against existing theories and empirical results in the literature and with industry standards. First, results reported here severely question the role played by managers' incentives in hedge funds performance. In a recent paper, Agarwal et al. (2009) test the hypothesis of a positive relationship between managers' incentives and hedge funds performance. Incentives are measured by total delta and, consequently, are high when the fund is at its high-water mark (maximum option delta). This contrasts sharply with our results, which indicate that outstanding performance is associated with funds that are far from the high-water mark (i.e., funds with very low option delta). Second, our results also challenge the validity of the drawdown-based performance measures (the Calmar and Sterling ratios) frequently used by practitioners. Our analysis makes it clear that hedge funds drawdowns contain more information about manager talent than the one summarized in the maximum historical drawdown. Furthermore, Figure 3.1 shows that it is the inverse of the Calmar and Sterling ratios that predict performance. This shows that, consistent with our analysis, large drawdown plays a better role as a proxy of talent than risk. In general, the main message of our analysis on this issue is that in the case of hedge funds, large negative returns (and survival) is very informative about talent and constitutes a very noisy proxy for risk. Third, on a more philosophical front, our analysis points to a paradox concerning the behavior of hedge fund investors: the Darwinian selection process cannot operate without a fairly high level of investor sophistication, but the huge inflows attracted by funds in the low drawdown decile suggest a fairly low level of sophistication because these funds, as a group, do not deliver outstanding performance. This dynamic may be explained, in part, by market segmentation whereby professional investors dominate participation in large drawdown funds and individual investors dominate in low drawdown funds. Alternatively, because we have looked at only aggregate figures, it may be that the large inflows to the low drawdown funds are mainly allocated to the good managers in the pool.

As a premier on the drawdown status of hedge funds, this paper leaves many issues unaddressed. First, our analysis focuses only on the analysis of the two extreme deciles; naturally, a more comprehensive analysis is a fruitful topic for future research. In particular, the analysis of the portfolio of funds that survive after hitting the highest drawdown decile, irrespectively of whether they stay in the highest drawdown decile (analyzed here) or move to lower deciles (not analyzed here) deserves special attention as it fits closer the Darwinian dichotomy between death and survival. Second, we believe that much could be learned by comparing the role played by drawdown status in hedge funds versus mutual funds. Some of our results here depend critically on the high-water mark clause, which is ubiquitous in the hedge fund industry but nearly absent in the world of mutual funds; hence, mutual funds are a good control group for testing our hypothesis. Finally, we believe the Darwinian selection process could be at place in many other corners of finance. One of the lessons that can be drawn from our analysis is that risk conditional on survival has dimensions beyond the standard notion of risk. To the extent that the Darwinian process may be operating in stocks, our theory may have some bearing on the debate on the value premium and the risk associated to financial distress.[11]

The balance of the paper is organized as follows. In Section 3.2 we analyze the economics behind drawdown status and state our hypotheses on the relationship between drawdown status and hedge fund performance. In Section 3.3 we describe the methodology employed and relate our analysis to the existing literature on hedge fund characteristics. Section 4.2 is dedicated to describing the data and defining the vari-

[11] On this front, it is important to notice the different opportunities open for investors to punish unfitted managers: while in hedge funds investors can do it by withdrawing funds at NAV, the mechanisms available in the case of stocks are very different.

ables used in our empirical analysis. In Section 3.5 we present our leading empirical results that corroborate the hypothesized relationship between drawdown status and hedge fund performance. In Section 3.6 we further explore the economics underlying the results obtained in Section 3.5 by testing the presence of insurance sellers in the lowest drawdown status portfolios, and the existence of a Darwinian selection mechanism among the funds in the largest drawdown decile. Section 3.7 is dedicated to robustness checks of our results. In Section 3.8 we set the analysis in the context of the standard regression methodology, and in Section 3.9 we include some concluding remarks.

3.2 The Economics of Hedge Fund Drawdown Status

The relationship between drawdown status and future performance would be relatively straightforward in a simple world of investment with just two types of long-lived traders: talented and untalented. We are aware that the word "talent" has many dimensions in investment management (and elsewhere). For instance, from a finalist perspective, a trader who delivers outstanding performance is no more talented than one who cannot deliver such performance but does succeed at raising a lot of capital. Indeed, both succeed at their core business (i.e., maximizing profits) and so must be endowed with a comparable amount of talent. That being said, in this paper, and more specifically in the context of the simple economy we describe next, we will view as talented those managers who can deliver outstanding performance in the form of pure (and persistent) alpha investing, and view as untalented those managers who deliver identically and independently distributed returns with zero mean each period. In this benchmark world, talented managers lie more often and more persistently in the lowest drawdown decile than untalented managers. This means that, in general, we should expect that portfolios of hedge funds drawn from the lowest drawdown decile outperform portfolios of hedge funds drawn from the highest drawdown decile.[12] Be means of a purely heuristic argument we can actually make even stronger and more precise predictions on the

[12] For limitations of scope and other reasons that will become apparent later on, in this paper we focus on analyzing the two extreme deciles. Note also that, abusing in the use of language, we will often refer to funds in the lowest (highest) drawdown decile as small (large) drawdown funds or funds with low (high) drawdown status.

expected performance of portfolios sorted on the basis of the past history of drawdown status:

- In the case of portfolio sorts on *one-lag* drawdown status (that is, each year's portfolio is sorted from the distribution of drawdowns of the previous year), we should expect the following prediction to hold:
  - **Prediction 1**: The lowest drawdown status portfolio will outperform the highest drawdown status portfolio. This follows because, at any given point in time, talented managers are more likely than untalented managers to hit the lowest drawdown decile. Hence, the relative pool of talented managers must be larger in the lowest than in the highest drawdown decile.
- In the case of portfolio sorts on T*-lag* drawdown status,[13] we should expect the following predictions to hold:
  - **Prediction 2**: The performance of the lowest drawdown status portfolios will increase in the length T of the lag. This prediction is based solely on the stronger return persistence of talented managers. Lucky untalented managers will only lie in the lowest drawdown decile transitorily. Hence, a requirement of lying in the low drawdown decile for several consecutive years will sort out most of the lucky untalented managers picked in the one-lag draw, and increasing the the lag will increase the odds that a manager remaining in the pool is talented.
  - **Prediction 3**: The performance of the highest drawdown status portfolios will decrease in the length T of the lag. This result follows using a symmetric argument to the previous one. Unlucky talented managers will only lie in the highest drawdown decile transitorily. Hence, a requirement that managers lie in the highest drawdown decile for several consecutive years will sort out most of the unlucky talented managers picked in the one-lag draw, which will increase the odds that a manager remaining in the pool is untalented.

[13]We define T-lag drawdown status as the intersection of deciles. For instance, a fund enters the 2-lag lowest drawdown decile portfolio in year t if it belongs *both* to the lowest decile of the drawdown distribution of year $t-1$ *and* to the lowest decile of the drawdown distribution of year $t-2$.

Of course, the world of hedge funds is considerably more complex than assumed in our benchmark economy, and in general we should not expect the data to support all of these predictions. Using our knowledge and experience in the world of investments, we can identify four main challenges to the assumptions behind our benchmark economy. Three are of an economic nature and either follow from well-known stylized facts about hedge funds or are a direct by-product of the incentives fees and high-water mark mechanism that characterizes the hedge fund industry; the fourth is related to the way in which hedge funds report to databases. We analyze each of these challenges in turn.

The first critical simplification in our benchmark economy is that it ignores the death of hedge funds. The death (or survival) of hedge funds is endogenous. In particular, many funds that experience large drawdowns die mainly because investors withdraw their money. If investors are able to sort talented from untalented managers during the period in which a fund experiences a large drawdown, then hedge funds managed by untalented traders will die faster. This means that the pool of talented managers in the largest drawdown sort may improve, rather than deteriorate, as we increase the sorting lag. Simply put: if, for instance, untalented traders are abandoned by investors one year after they hit the highest drawdown decile, then they will be selected in the one-lag sort, but not in any of the other lagged shorts. Hence these longer lagged sorts in the highest drawdown decile will tend to be more dominated by unlucky talented managers. All this means that Prediction 3 could be reversed when hedge funds survival is endogenous. This is one of the key insights to be derived from this paper. The market may operate a Darwinian selection mechanism whereby talented managers (the fittest) are more likely to survive several periods after large drawdowns. Remarkably, this selection mechanism is incentive compatible for old investors, because of the industry's incentive structure, and for talented managers. As we explained in the introduction, old investors in a fund experiencing large drawdowns have two choices: stay in or leave and move to a new fund. If they stay in, they will save a lot of money in incentive fees as these will not be charged until the fund goes back to the high-water mark; if they leave, they will start at the high-water mark in the new fund and will pay incentive fees as the fund realizes positive returns. Obviously the incentive fees game plays in favor of staying in, but only when the expected return of the fund is positive; that is, when the manager is talented.

Hence, these are times when it is worthwhile gathering extra relevant information on the manager's investment philosophy and strategy. But it is also optimal for talented managers to be less opaque on their investment philosophy. Not doing so would probably result in the exit of investors and the death of the fund. As stated before, this interaction between investors and managers can result in a *Darwinian selection process*, whereby only the most talented managers survive. In this case, performance would be increasing, rather than decreasing, in the length of the lag used to sort funds in the 10th decile (largest drawdowns).

The second key assumption that could be violated in the real world is that of lack of persistency in the returns of untalented managers. Under this assumption, untalented managers only hit the low drawdown decile transitorily. However, as we previously mentioned, due to the high-water mark clause, all managers are interested in hitting the low drawdown status as often as possible. Being endowed with talent is one way of achieving this. There are, at least, two well-known alternatives. First, fund managers can specialize on "insurance selling" like strategies.[14] These strategies resemble a dynamic strategy of rolling over short positions in deep out-of-the-money put options on some broad stock or commodity index. All of them share the property of delivering positive returns in normal times with the (hidden) cost of large loses in turmoil times. By its own nature, these strategies set the fund in the lowest drawdown decile most of the time. But they are very different to the strategies of talented investors, as they are not associated to outstanding performance when properly accounting for the true risk of the strategy. Hence, *insurance sellers* are missing in our benchmark economy as they would correspond to the case of untalented traders with persistent returns in the lowest drawdown decile. Their presence in the real world will tend to deteriorate the performance of the low drawdown status portfolios when measured in samples that include crisis periods. On the other hand, another way of reaching the lowest drawdown status frequently without talent consists on implementing a sound risk control technology.[15] Although these traders seldom deliver large returns, they tend to lie in the low

[14]For instance, see Lo (2001), and Jorion (2007), for further details on these strategies.

[15]The risk control technology can be specified in terms of value at risk or, even, maximum drawdown constraints. The optimization problem in the presence of such constraints has been widely analyzed in the literature: see, for example Grossman and Zhou (1993), Cvitanic and Karatzas (1995), Lopez de

drawdown decile as large drawdowns are explicitly avoided. In sum: at any time the lowest drawdown decile may be contaminated (relative to our benchmark economy) by the presence of funds, that mimic low drawdown funds, managed by untalented traders who use various techniques to maximize fees.[16] Since these funds are not associated with outstanding performance, a strong presence of these funds in the lowest drawdown decile will damage the performance of the lowest drawdown portfolio sorts up to the point of possibly reversing predictions 1 and 2. It is worthwhile mentioning that the presence of these mimicking funds can be partially tested. For instance, insurance sellers tend to experience very large losses during periods of crisis; therefore, if such losses are larger for the lowest drawdown decile portfolio than for the HFR portfolio then we could infer that the former was more heavily populated by insurance sellers.

The third key assumption in our benchmark economy is the absence of systematic risk in the strategies of both talented and untalented traders. The title "Talent Required"[17] of an article on hedge funds by Sanford Grossman in the Wall Street Journal probably reflects the essence of this industry: talent is assumed but is probably not always there. Indeed, it is well known that the industry offers some alpha, but mainly a lot of beta investing, what has given rise to a growing literature on hedge fund replication.[18] Introducing systematic risk alters our benchmark economy in several ways. First, it makes the lowest decile extremely crowded during "normal" periods –that is, most of the time.[19] Second, we expect that systematic risk will intensify the Darwinian selection process described previously. Recall that the drawdown status ranks funds with respect to other funds in the market. In the presence of systematic risk, large drawdown funds are specially singled out in normal times, which facilitates both the researching and identification of the talented ones among these funds.

Prado and Peijan (2004), and Gaivoronski and Pflug (2005).

[16]This last statement must be understood in the context of our definition of talented versus untalented managers. We are not associating the use of risk control techniques with a the lack of talent in asset management. Some talented managers may also use a sound risk control technology, and doing so would place them in the lowest drawdown decile even more often than otherwise. The presence of these does not alter the predictions of our benchmark economy.

[17]The Wall Street Journal, September 29, 2005, Page A18.

[18]For instance, see Leibowitz (2005) and Hasanhodzic and Lo (2007).

[19]Observe that the lowest decile will tend to be very crowded at every point in time because it picks all the funds with a good track record and a non-negative current return, without regard to how large the current return is.

The fourth possible deviation from our benchmark economy is related to the way in which hedge funds report to databases. First, it is well known that funds tend to enter data sets after several periods of good performance, and that this performance is backfilled. In terms of our economy, this backfilling bias will result again in the overcrowdness of the low drawdown decile with funds that are not necessarily managed by talented traders. Second, some very successful funds cease reporting to databases when they are no longer interested in attracting investors. This may occur because the fund has reached the maximum allowed number of investors or because the manager believes that additional capital would deteriorate performance given his investment niche. In terms of empirical studies that rely on information from databases, such funds "die" (as they stop reporting) of success rather than failure. Since these successful funds most likely lie in the lowest drawdown decile they could be missed in the sequentially increasing lagged sorts. For example, if a very successful fund stops reporting one year after it hits the lowest drawdown decile, it will be picked in the one-lag sort, but not in any of the other lagged sorts. Thus, the *stop reporting process* operates in exactly the opposite direction to the Darwinian selection process, although it affects the lowest rather than the highest drawdown sorts. In terms of our predictions, if the stop reporting process is very intense, then Prediction 2 could be reversed.

We are now in a position to advance and interpret the most important results of our analysis. Using the universe of hedge funds in the HFR data set, we find that:

- On average, 72% of the funds have a drawdown equal to zero and so belong to the lowest drawdown decile. This confirms the lowest drawdown decile as an "absorbing" decile. It is explained by its own definition and is consistent with the existence of substantial systematic risk in hedge funds strategies, the backfilling bias and, more importantly, with the existence of many mimicking funds that implement either insurance-selling strategies or pure tight risk control techniques.

- The lowest drawdown status portfolio *underperforms* the highest drawdown status portfolio. This is just the opposite of what is expected in our benchmark economy. We interpret this as confirming that the lowest drawdown decile is highly contaminated by mimicking funds. Furthermore, the lowest drawdown portfolio underperforms the HFR portfolio, especially during periods of crisis. We interpret this result as corroborating a significant presence of insurance sellers in the lowest drawdown decile.

- Performance is monotonically increasing in the length of the sorting lag for the high drawdown status portfolios. This too is the opposite of what is expected in our benchmark economy. The evidence supports the existence of a strong and efficient Darwinian selection process, which is corroborated by a closer examination of the hedge funds included in the sorted portfolios.

- No clear pattern is found in the relationship between the length of the sort lag and the performance of portfolios in the lowest drawdown decile. This finding is consistent with the over-crowdedness of that decile and with the interaction between the self de-reporting process and the presence of mimicking funds.

In the next section we introduce some formal definitions and discuss the methodology employed in this paper. We also relate our work to the existing literature on hedge funds characteristics and performance.

3.3 Methodology and Related Literature

Our paper contributes to the literature on hedge fund characteristics and performance on two fronts. First, it introduces the drawdown status of hedge funds as a new and important characteristic related to performance. Second, from a methodological point of view, it deviates from the standard regression analysis and uses the portfolio sort methodology to identify outstanding performance.[20] We now turn to analyze these two issues in more detail.

We first define $NAV_{i,t}$ as the net asset value of hedge fund i at the end of measurement period t. We assume that all hedge funds use annual measurement periods and,

[20]In any case, as previously stated, we also verify our results using the more conventional regression setting.

consequently, $NAV_{i,t}$ corresponds to the net asset value of fund i at the end of December of year t. Then, the *drawdown* of hedge fund i at the end of year t is defined as

$$D_{i,t} \equiv 1 - \frac{NAV_{i,t}}{Max_{\tau \leq t} NAV_{i,\tau}}, \tag{3.1}$$

where τ applies to all years from fund i's inception date. Under this definition, $D_{i,t}$ lies in the interval $[0, 1]$. When $D_{i,t} = 0$, the fund has set a new high-water mark at the end of year t. When $D_{i,t} \neq 0$, the fund is below the high-water mark. The high-water mark clause directly links $D_{i,t}$ to the fees managers raise (and investors in the fund pay).[21] When $D_{i,t} = 0$, the manager collects incentives fees in year t both from old investors as well as new investors (year t investors) in the fund.[22] When $D_{i,t}$ is close to one, the fund ends the year very far from the high-water mark. Old investors in the fund are not paying incentive fees currently and very likely will not pay them in the near future. Hence, roughly speaking, from the investors point of view, $D_{i,t} = 0$ is associated to funds which are relatively expensive in the present and also very likely in the near future, while $D_{i,t}$ close to one is associated to funds which are cheap in the present and very likely in the near future too for old investors. Finally, notice that there is not a one to one relationship between $D_{i,t}$ and the fund return in year t. We only know that $D_{i,t} = 0$ is associated to funds whose return for the year is non-negative. But it may apply to funds whose returns are arbitrarily large or low. On the other hand $D_{i,t} \neq 0$ is consistent with positive and negative returns during year t, even when $D_{i,t}$ is very close to one.

The *drawdown status* of fund i at date t is just the decile $D_{i,t}$ belongs to in the distribution of the drawdowns of all hedge funds in the economy at date t. In this paper we analyze the relationship between the current and past drawdown status of hedge funds and their future performance. The general treatment of this problem is complex and, definitively, beyond the scope of this paper that mainly aims to introduce

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[21] In our sample, 91,6% of the funds have a high water mark clause. In the discussion that follows we implicitly assume that the fund does not have a hurdle rate. The relationship between $D_{i,t}$ and fees in the presence of a hurdle rate is very similar, with the only noticeable difference of the stronger requirement of the fund return being larger than the hurdle rate, instead of being larger than zero, in order for the manager to be able to collect the incentive fee.

[22] Strictly speaking, there is the critical case of $NAV_{i,t-1} = NAV_{i,t} = Max_{\tau \leq t}\ NAV_{i,\tau}$, for which $D_{i,t} = 0$ but the manager does not collect incentives fees, as the fund return for year t is zero.

the subject and present very appealing results to the academic debate. For this reason we restrict our attention to the analysis of hedge funds for which our analysis in the previous section provides sharp predictions. In particular, we focus on the analysis of hedge funds in: 1) the two extreme deciles, $d = 1$ and $d = 10$; and, 2) in the intersection of consecutive deciles. Formally, with $DS_{d,t}(T)$ we denote the set of all funds that belong to the drawdown decile d in the T consecutive years preceding and including year t. For example, $DS_{10,t}(1)$ is the set of all hedge funds in the 10^{th} drawdown decile of year t; $DS_{1,t}(3)$ is the set of all hedge funds that belong to the intersection of the 1^{st} drawdown decile of years t, $t-1$ and $t-2$; and so on. Due to data limitations, we will further restrict our analysis to the case of three lags, $T \leq 3$.

In order to test the relationship between drawdown status and performance, we adopt a portfolio sort approach. The portfolio sort approach is not new, but rather the contrary. It is the most standard and widely used approach in the literature on asset pricing anomalies.[23] In this context, the analysis starts with an assumed asset pricing model, which currently mainly consists of a four-factor specification which includes the three Fama and French (1993) factors plus a fourth momentum factor. Then portfolios of securities sorted on a variety of economic variables are tested in the context of the asset pricing model.[24] In this paper we adopt this approach to assess the outstanding performance of portfolios sorted according to hedge funds past drawdown status. To do this we assume the most widely accepted model of performance evaluation in the hedge fund literature, the Fung and Hsieh (2004) seven-factor model. This model builds on the original Sharpe's style regression model (Sharpe (1992)) and assesses performance in a risk-adjusted manner while accounting for hedge funds' investment styles and heavy use of non-linear strategies. The model exhibits a very high explanatory power.[25]

[23]It has also been used recently for hedge fund performance analysis in Jagannathan et al. (2010).

[24]The set of sorting variables used in the literature is very large, including many accounting variables, such as accruals (Sloan (1996), profitability (Haugen and Baker (1996) and Cohen, Gompers, and Vuolteenaho (2002)), asset growth (Titman, Wei, and Xie (2004)), pension plan funding status (Franzoni and Marin (2006), and net stock issues (Daniel and Titman (2006)), and many other variables, such as the stock's past returns (Jegadeesh and Titman (1993)), etc. For a summary of the current debate on pricing anomalies and the use of the portfolio sort methodology see Fama and French (2008).

[25]See Fung and Hsieh (2001, 2004), Kosowski, Naik and Teo (2007), Fung et al. (2008), Bollen and Pool (2009) and Jagannathan et al. (2010).

In the Fung and Hsieh (2004) seven-factor model, hedge fund excess returns are regressed on the following factors: the excess return on the S&P 500 index (SNP); a small minus large factor (SizeSpr) constructed as the difference between the returns of the Wilshire Small Cap 1750 Index and the Wilshire Large Cap 750 Index; the excess returns on portfolios of lookback straddle options on currencies (FXOpt), commodities (ComOpt), and bonds (BdOpt), which are constructed to replicate the maximum possible return to trend-following strategies on their respective underlying assets; the excess return on Fama treasury bond portfolio with maturities greater than 10 years (Bd10Yr) and the excess return on the CitiGroup Corporate BBB 10+yr index less Bd10Yr (CredSpr).[26] Hence, the performance of a portfolio of hedge funds i is assessed by inspecting the "alpha" in the following model:

$$\begin{aligned} R_{i,t} = \alpha_i + \beta_{i,1} SNP_t + \beta_{i,2} SizeSpr_t + \beta_{i,3} FXOpt_t + \beta_{i,4} ComOpt_t \\ + \beta_{i,5} BdOpt_t + \beta_{i,6} Bd10Yr_t + \beta_{i,7} CredSpr_t + \epsilon_{i,t} \end{aligned} \quad (3.2)$$

where $R_{i,t}$ is the excess return of portfolio i during period t.

In our empirical exercise we create both equally and value weighted portfolios that at each year t hold all the hedge funds in the corresponding $DS_{d,t-1}(T)$. More specifically, using the information available in December of year t we sort funds into deciles and then form portfolios in January of year $t+1$. These portfolios can be viewed as anticipating because the information arrives to the data providers several months after January.[27] In any case, in order to avoid suspicions on the results being driven by the use of anticipating information, in not tabulated results available from the authors upon request, we verify that none of our results change significantly when portfolios are formed at the beginning of May of each year. The reason for this is obvious. Unlike stocks, where the portfolio formation date is critical because information is impounded into prices very fast, in hedge

[26]Some of the factors in the original Fung and Hsieh (2004) model were not tradable. Following Sadka (2010) critique to the use of these factors, in this paper we substitute the not tradable factors with the tradable ones used in Jagannathan (2010). We have verified, however, that our results hold when using the original Fung and Hsieh (2004) factors (results are available from the authors upon request).

[27]This is the case for several reasons. First, although HFR database provides a flash update at the beginning of each month, most of the data is missing as the funds report the data later during the month. Second, managers often send corrections to data previously reported. Indeed, HFR states that data is subject to revision during the trailing four months.

funds shares are marked at the fund's NAV. Hence, information related to the talent of the manager will only be revealed slowly over time as the NAV reflects the manager's trading skills. For this reason, the differences in performance between the January and May portfolios should be small and mainly obey to considerations such as the different lifespan of the portfolios or the asymmetric death of funds in the portfolios.[28] Once portfolios are formed, we compute the monthly returns and estimate model (3.2). Fung et al. (2008) extend model (3.2) allowing for time variation in risk exposures arising from structural breaks. We have also analyzed this modified version in Section and have verified that all our results hold.

Setting up performance evaluation in the context of the portfolio analysis methodology presents several advantages. First, the methodology is very versatile and allows for a rich set of variables to be tested. Furthermore, it allows to assess if hedge funds performance is outstanding in a risk-adjusted manner. It also presents some inconveniences. In particular, unlike the case of securities where the market portfolio exhibits no alpha, it turns out that the portfolio that includes all hedge funds in the HFR data set (the HFR portfolio) exhibits a strictly positive alpha. For this reason we refer to outstanding performance as an alpha above the one of the HFR portfolio. As noted in the introduction, both methodologies suffer from an identification problem when applied to the hedge fund characteristics-performance debate. To alleviate this problem, we rely on the use of conditional sorts, in the portfolio sorts methodology, and include all controls that the literature has suggested so far, in the regression analysis. For all these reasons we strongly believe that these two approaches complement each other and must be taken into account in the analysis of hedge fund characteristics. As we will see, all our results survive both methodologies, what place drawdown status as a genuine hedge fund characteristic related to performance.

The literature on hedge funds characteristics is too large to cover in detail here. The consensus so far is that the following hedge fund characteristics are related to performance: size (Brorsen and Harri (2004), Getmansky (2005), Ammann and Moerth

[28]This would not be the case if portfolios were formed using shares of funds that trade in secondary markets. In this case, like in the case of stocks, the use of non-anticipating information at the portfolio formation date is key.

(2005)), age (Liang (1999), Howell (2001), Amenc and Martellini (2003)), managerial incentives measured using fee structure (Ackermann, McEnally, and Ravenscraft (1999), Liang (1999), Edwards and Caglayan (2001)) or using delta (Agarwal et al. (2009)), fund provisions (Liang (1999), Agarwal et al. (2009)), past performance (Agarwal and Naik (2000), Bares, Gibson and Gyger (2003), Baquero, Horst and Verbeek (2005), Jagannathan et al. (2010)), flows (Getmansky (2005), Agarwal et al. (2006), Fung et al. (2008)), strategy (Amenc and Martellini (2003), Brown and Goetzmann (2003)) and volatility (Schneeweis (1998), Le Moigne and Savaria (2006)).[29] In Section 3.8 we use all these variables as controls when assessing the relevance of drawdown status as a performance related characteristic.

3.4 Data and Variable Construction

3.4.1 Data

Data on hedge fund performance and characteristics is provided by Hedge Fund Research Inc. (HFR). HFR builds its dataset based on surveys of hedge fund managers. Funds report to HFR mainly for marketing purposes, because they are prohibited from public advertisement. HFR tracks data on hedge funds from 1992, and from 1994 onwards keeps records of hedge funds that either stop reporting or are liquidated. As of May 2010, HFR covers 10,931 hedge funds in its database.[30] All funds are classified into the "active" and "dead" funds categories. In our study, active funds are those that are reporting as of May 17, 2010. Once a fund is no longer reporting or liquidated, it is transferred to the dead funds category. Out of these 10,931 funds, 4,427 are classified as active funds, and 6,504 as dead funds.

HFR reports the monthly time series of returns, assets under management (AUM)

[29]See Agarwal and Naik (2005) and Gehin (2006) for a review of main findings on hedge fund characteristics. Le Moigne and Savaria (2006) compare the relative importance of thirteen hedge fund characteristics in explaining the cross-sectional variations and find that style, performance, volatility and fee structure are the most important characteristics.

[30]This figure does not include a total of 4102 funds of funds which are also covered by HFR but not included in our analysis.

and net asset value (NAV) of the hedge funds in its database. Monthly returns are defined as the change in net asset value during the month divided by the net asset value at the beginning of the month. Most of our analysis is performed at a monthly frequency. For this reason we drop 146 funds that report returns quarterly, 24 funds that have missing return values during reporting period and 47 funds that do not report returns at all.[31] This leaves us with 10,714 funds. We do a similar revision for assets under management. Unfortunately, 2,046 funds do not report AUM at all and 943 funds report AUM with missing or zero year-end values.[32] Dropping these funds reduces the sample to 7,725 funds. Most of the funds do not report NAVs. However, following the method employed by TASS database, we can backfill NAV values from reported return values.[33]

Along with the time series variables, HFR database reports funds characteristics. These include management fees, incentive fees, lockup period, redemption period, advance days notice, hurdle rate and high-water mark provisions. Fund characteristics are reported one-time and, consistent with prior research, in our analysis we assume that hedge funds have kept these structures unchanged through time.[34] A total of 135 hedge funds have missing information related to these fund characteristics. Dropping them reduces the sample to 7,590 funds.

Returns can be reported net of all fees, net of only management fees or gross of all fees. In our sample, 98% of the returns are reported net of all fees. Following standard

[31]None of these funds reported NAV when return was not reported, so we were unable to recuperate missing returns from NAV.

[32]A total of 50 funds that have year-end AUM value set at zero (during their reporting period) are eliminated as these would create problems in the formation of portfolios, as well as in the computation of the *Flow* variable.

[33]Liang (2000) provides an in-depth explanation on this issue. For the funds that do not report NAV, TASS assigns some hypothetical initial NAV and then backfills the missing NAVs from the initial NAV and return numbers. HFR does not backfill the missing NAVs.

[34]Liang (2001) argues that hedge funds seldom modify their fee structure. He shows that less than 1% of the funds in his sample changed their fee levels from 1997 to 1998, and that the change was related to poor performance during 1998 financial crisis. We perform a similar study using characteristics reported to HFR as of March 2007 and May 2010. We find that less than 1.4% (2.8%) of the funds in the sample have changed their incentive fee (management fee) structure during this period. These numbers are very low considering that the period under study embeds the recent financial crisis which had significant negative effects in hedge fund performance. Hence, we believe that assuming fund characteristics to be fixed will not have any significant effect on our analysis. Similar results hold for other fund characteristics.

practice in academic studies, we consider only funds that report returns net of all fees, which leaves us with a sample of 7,408 funds. The vast majority of the funds report returns and assets under management in US Dollars. Dropping the remaining funds that report variables in different currencies leaves us with a sample of 6,540 funds.

The fee structure of hedge funds requires further data filtering. Incentive fees are based on performance over a predefined period, which in most cases is one year. Within a few months after the period is over, the monthly return data is corrected by fund management to be reported as net of all fees. This updated data is then sent to data vendors; hence it is important to leave a lag between data download and data analysis periods.[35] Consistent with this fact, HFR states that "the trailing four months of performance are subject to revision as HFR receives updates from lagged funds".[36] On account of these two facts, we decide not to include 2010 data in our analysis.

We further restrict the sample period in order to mitigate the well known survivorship bias. The survivorship bias is the tendency to exclude failed funds in performance studies, eventually leading to incorrect results. As HFR tracks failing funds since 1994, our final sample period covers the period January 1994 to December 2009. Given this period, we require funds to have 3 lags of annual variables defined in order to be included in the study. This implicitly restricts the sample to funds with at least three consecutive years of history. Our main goal in this restriction is to keep the universe of funds across portfolios fixed. Furthermore, the requirement of a two or three year length of return history is applied in all the previous studies in the hedge funds literature.[37] This is mainly done to ensure that each fund has a long enough corrected time series for meaningful regression results. Agarwal and Naik (2005) note that multi-period sampling bias occurs because academic research requires a minimum of 24 month or 36 month returns for a fund to be included in the sample. However, Fung and Hsieh (2000) find that this bias is small with its magnitude being close to 0.6% when a 36 month minimum return history is imposed.

[35] See Ackermann et al. (1999) for a detailed explanation.

[36] See HFR Indices Basic Methodology and FAQ available at http://www.hedgefundresearch.com/index.php?fuse=indices-faq&1285989513.

[37] Note that requirement of two years return history is also implicitly applied in all studies where annual variables are regressed on lagged annual variables.

The final sample includes 3,540 hedge funds during the period 1994-2009 with basic fund characteristics and 3 lags of annual variables defined. Of these funds, 1,644 are active, 877 are not reporting and 1,019 are liquidated.

3.4.2 Variable Construction

In addition to the drawdown related variables defined and discussed before, in this paper we also use other variables either for portfolio sorting or as controls in the regression analysis. In particular, the following variables are used in the present paper: flow, total delta, fees, gross return, age, volatility, alpha, Sharpe ratio, Calmar ratio, and Sterling ratio.

In the construction of variables, we closely follow Agarwal et al. (2009), introducing natural modifications for the new variables used in this paper. We define the *monthly dollar flow* of fund i in month t as:

$$\textit{Monthly dollar flow}_{i,t} = AUM_{i,t} - AUM_{i,t-1}(1 + \textit{Return}_{i,t}).$$

Annual dollar flow of fund i in year t is the sum of the monthly dollar flows during year t. The *flow* for a portfolio (P) in year t is the sum of the annual dollar flows of the funds in the portfolio scaled by the total AUM of the funds in the portfolio at the end of the previous year:[38]

$$Flow_{p,t} = \frac{\sum_{i\epsilon P} \textit{Annual dollar flow}_{i,t}}{\sum_{i\epsilon P} AUM_{i,t-1}}.$$

Total delta is the total expected dollar change in the manager's compensation for a 1% change in NAV of the fund at the end of year. It is the summation of the delta from investors' assets (option delta) and the delta from the manager's coinvestment assuming

[38] An exception to this definition is used in the regression analysis. Since we are following the regressions performed in Agarwal et al. (2009) where the analysis is done on an annual basis, we use their definition of *Flow* in the regression analysis. Here, the *Flow* of fund i is defined as the net dollar flow into the fund in year t, scaled by AUM of the fund at the end of the year $t-1$:

$$Flow_{i,t} = \frac{AUM_{i,t} - AUM_{i,t-1}(1 + \textit{Return}_{i,t})}{AUM_{i,t-1}}.$$

that manager reinvests in the fund all incentive fees collected over time. The computation of deltas requires the computation of fees and gross returns simultaneously and then use of Black-Scholes option pricing formula. See Appendix A in Agarwal et al. (2009) for the details of the computation. Note that option delta of the fund is the sum of the deltas from different sets of investors, each of whom have their own exercise price depending on when they entered the fund (which determines the high-water marks that apply to each investor). Hence, the computations are derived by tracking the entry/exit of investors in the funds according to the funds' net flows. Once annual fees are computed, we add back one-twelfth of this each month for the past year to deduce monthly *gross returns*, as in Agarwal and Naik (2000). *Volatility* is the standard deviation of the monthly returns of the fund for a given year. *Age* is the age of the fund at the end of the year. In our portfolio analysis, as in other studies, we focus on the intercept directly obtained from the Fung and Hsieh (2004) seven-factor regressions. We denote this intercept as *alpha* and perform comparative analysis on its value and t-statistics.[39]

We follow Kestner (1996) for the computation of the Sharpe, Calmar and Sterling ratios. *Sharpe ratio* is defined as the average monthly excess returns divided by the standard deviation of the excess returns (excess of risk free rate). To facilitate comparison with Calmar and Sterling ratios, in the construction behind Figure 3.1 we calculate it for a three-year period. *Calmar ratio* is defined as the average annual return over the past three years divided by the maximum drawdown (*MaxD*) suffered over these three years:

$$Calmar_{i,t} = \frac{(Return_{i,t} + Return_{i,t-1} + Return_{i,t-2})/3}{MaxD_{i,t-2\to t}}.$$

Finally, *Sterling ratio* is defined as the average annual return over past three years divided by average annual maximum drawdown over three years and 10% is added to

[39] An exception is done in the analysis of characteristics based portfolios reported in Figure 3.1. Here, to obtain results comparable with those in Agarwal et al. (2009), *Monthly alpha* is estimated from the fund-level time-series regression of excess returns on Fung and Hsieh (2004) seven factors, allowing for structural breaks, and includes both the regression intercept and the regression residuals. *Annual alpha* is the sum of the monthly alphas in a given year.

the denominator:

$$Sterling_{i,t} = \frac{(Return_{i,t} + Return_{i,t-1} + Return_{i,t-2})/3}{(MaxD_{i,t} + MaxD_{i,t-1} + MaxD_{i,t-2})/3 + 10\%}.$$

3.4.3 Summary statistics

In Table 3.1 we report the descriptive statistics of all variables used in the analysis. The results show that our sample shares the main properties of other samples used elsewhere, including papers that use a larger set of funds. For instance, the comparison of our summary statics and those in Agarwal et al. (2009)[40] reveals that our funds are very similar in terms of average returns, lockup period, restriction period, age, fees and volatility. We notice that the presence of the high-water mark clause is more frequent in our sample (91.6% of the funds) than in theirs (80.1% of the funds) and that hurdle rates are much less frequent in our sample (12% versus 60.8%). The three most relevant differences relate to size, flows and the incentive related variables. In particular, our funds are relatively larger ($167 millions vs. $120.6 millions of AUM on average), receive more inflows as a percentage of AUM (173% vs. 120% on average) and have a larger average managerial ownership (11.6% versus 7.1% of AUM), option delta ($174.9 millions versus $100.1 millions) and total delta ($331.4 millions versus $188.8 millions). We believe these differences do not arise from a significant different composition of funds in the samples but rather from the fact that in our sample we include the period 2003-2009. During this, mostly bullish, period many funds grow in terms of AUM, receive large inflows and experience returns that get them closer to their high-water marks, what explains the larger option and total deltas.

[40] This paper uses a very comprehensive data set obtained as the union of funds in the CISDM, HFR, MSCI and TASS databases.

Table 3.1: **Summary Statistics of HFR Filtered Data Set**

This table reports the summary statistics of HFR filtered data set. The sample period is 1994-2009. *Returns* are the annual returns of the fund net of all fees. *Gross returns* are the annual gross returns of the fund derived from net returns after taking into consideration fees, inflows and fund provisions. *Drawdown* is one minus the ratio of the fund's net asset value (NAV) to its maximum reached over the fund's entire history. *Total delta* is the total expected dollar change in the manager's compensation for a 1% change in the fund's NAV. *Option delta* is the manager's delta from investors' assets in the fund. *Managerial ownership* is the ratio of the manager's investment in the fund to the AUM of the fund. *Hurdle rate* is a provision that allows the manager to collect incentive fees only above a pre-specified rate of return. *High-water mark* is a provision that allows the manager to collect incentive fees only after recovering all past losses if they exist. In the table, we report the percentage of funds that have *hurdle rate* and *high-water mark* provisions. *Lockup period* is the pre-specified period of time that an investor cannot redeem her shares after investing in the fund. We report its statistics for the subsample of funds that impose lockup period. *Restriction period* is given by the sum of the *advanced days notice* and *redemption period*, where *advanced days notice* is the pre-specified period of time that the investor must notify the fund's managers of her intent to withdraw money and *redemption period* is the time she has to wait to get her money after advanced days notice is over. *Flow* is the net dollar flows into (or out of, if negative) the fund during the year, scaled by AUM of the fund at the end of the year. *Volatility* is the annualized standard deviation of the monthly returns of the fund during the year. *Age* is the age of the fund in years. *Management fee* is the percentage of fund's net AUM that is paid annually to the fund management for administering the fund. *Incentive fee* is the percentage of annual profits captured by the fund management in reward for positive performance and is defined over some benchmark or high-water mark.

Fund Characteristics	Mean	Std. Dev.	25th Percentile	Median	75th Percentile
Returns (% per year)	12.9	34.5	1.4	9.7	20.4
Gross returns (% per year)	15.9	41.7	1.7	11.5	24.4
Drawdown (% per year)	5.3	13.0	0.0	0.0	2.1
Total delta ($'000)	331.4	1064.7	15.3	65.9	245.1
Option delta ($'000)	174.9	563.2	5.8	31.9	125.6
Managerial ownership (% of AUM)	11.6	19.6	1.6	4.8	11.8
Hurdle rate (% of funds)	12.0				
High watermark (% of funds)	91.6				
Lockup period (years)	1.0	0.5	1.0	1.0	1.0
Restriction period (years)	0.3	0.3	0.2	0.3	0.4
Flow (%)	173.2	8935.8	-17.0	4.6	53.5
AUM ($M)	167.0	481.6	11.1	39.3	130.0
Volatility (%)	3.8	3.5	1.6	2.9	4.9
Age (years)	5.5	3.9	2.7	4.5	7.3
Management fee (%)	1.5	0.7	1.0	1.5	2.0
Incentive fee (%)	19.1	5.0	20.0	20.0	20.0

Table 3.2: **Main Characteristics of the 6 Drawdown Status Based Portfolios**

This table reports the main characteristics of the six drawdown status based portfolios. The sample period is January 1996-December 2009. At the end of each year t, we sort the drawdown of funds into ten deciles. Lowest drawdown status (DS) Lag 1 portfolio is the the set of all hedge funds in the 1^{st} drawdown decile of year $t-1$. Highest drawdown status Lag 1 portfolio is the the set of all hedge funds in the 10^{th} drawdown decile of year $t-1$. Lag 2 portfolios are the set of all hedge funds that belong to the intersection of the corresponding drawdown decile of years $t-1$ and $t-2$. Lag 3 portfolios are the set of all hedge funds that belong to the intersection of the corresponding drawdown decile of years $t-1$, $t-2$ and $t-3$. *Number of funds* is the total number of funds in the portfolio at the beginning of formation period. *Annual dollar flow* is the annualized net dollar flows into (or out of, if negative) the funds in the portfolio during the year. See Table 3.1 for the definition of variables. Regarding number of funds and AUM, we report their percentages over corresponding HFR portfolio values in parenthesis. The percentages reported in parenthesis for dollar flow, total delta, option delta, manager delta and incentive fees are defined over their portfolio values. To facilitate comparison, we report the averages of the all variables over 14 years. All numbers are rounded to the nearest integer (for precision, numbers that are less than one percent are are rounded to the first decimal in percentage).

	Lowest DS Portfolios			**Highest DS Portfolios**			**HFR**
	Lag 1	Lag 2	Lag 3	Lag 1	Lag 2	Lag 3	
Number of funds	752	648	567	109	51	29	1089
	(72%)	(61%)	(53%)	(10%)	(5%)	(3%)	(100%)
AUM ($M)	164,081	151,871	140,907	8,269	2,008	775	211,212
	(80%)	(71%)	(64%)	(5%)	(2%)	(0.4%)	(100%)
Annual dollar flow ($M)	17,011	18,849	17,362	-1,182	-754	-194	11,164
	(12%)	(17%)	(18%)	(-10%)	(-24%)	(-16%)	(7%)
Total delta ($M)	359	331	305	14	4	2	431
	(0.3%)	(0.3%)	(0.3%)	(0.1%)	(0.1%)	(0.2%)	(0.2%)
Option delta ($M)	196	184	173	4	1	0.4	222
	(0.1%)	(0.2%)	(0.2%)	(0.0%)	(0.0%)	(0.0%)	(0.1%)
Manager delta ($M)	163	147	133	10	3	1	209
	(0.1%)	(0.1%)	(0.1%)	(0.1%)	(0.1%)	(0.1%)	(0.1%)
Incentive fees ($M)	3,521	3,210	2,953	12	11	6	3,546
	(3%)	(3%)	(3%)	(0.2%)	(0.6%)	(1%)	(2%)
Mean age (years)	6.3	6.3	6.1	6.6	6.9	7.3	6.4
Mean lockup period (years)	0.3	0.3	0.3	0.3	0.4	0.4	0.3
Mean restriction period (years)	0.3	0.3	0.3	0.3	0.3	0.3	0.3

3.5 Drawdown Status and Performance: Portfolio Sorts Analysis

In this section we analyze the relationship between hedge fund drawdown status and performance using the portfolio sort methodology. We study a total of 6 portfolios corresponding to the two extreme deciles, $d = 1$ and $d = 10$, for lags 1, 2 and 3. These are the portfolios that at each period $t + 1$ hold all hedge funds that belong to the corresponding sets $DS_{d,t}(T)$, for $d = 1, 10$ and $T = 1, 2, 3$. In Table 3.2 we collect the basic properties of the funds included in these 6 portfolios.[41]

Table 3.2 already reveals some very interesting properties of drawdown based portfolios. First notice that, as conjectured in Section 3.2, the lowest drawdown status portfolios are over crowded. On average, during the period January 1996 to December 2009, 72% of the funds have a one-lag drawdown equal to 0. This means that on a typical year, 72% of the funds in the sample end the year setting a new historical high-water mark. In principle, this stylized fact is consistent with both the existence of a lot of talent in the hedge fund industry and the existence of a lot of mimicking funds which, as we argued in Section 3.2, basically consist of untalented insurance sellers and (pure) risk managers. The large figure is also explained by a lot of systematic risk in hedge funds strategies. Also as expected, funds in the lowest drawdown decile are much larger than funds in the highest drawdown decile. Furthermore, while the former attract large inflows, the latter suffer capital outflows. Even more interestingly, low drawdown status funds have a much larger total delta and charge much more money in incentive fees than funds in the highest drawdown decile, which from an incentive perspective should result in superior performance, according to the *managers incentives hypothesis* (Agarwal et al. (2009)). Finally, regarding investment styles, the largest drawdown status portfolios are relatively more populated with equity-hedge funds and relatively less populated with event driven, macro and relative value funds.

[41] Notice that the sample period for the portfolios is January 1996-December 2009. This is due to the requirement of having at least 200 funds in any given year in order to have meaningful portfolio sorts. By January 1996 the sample included a total of 222 funds.

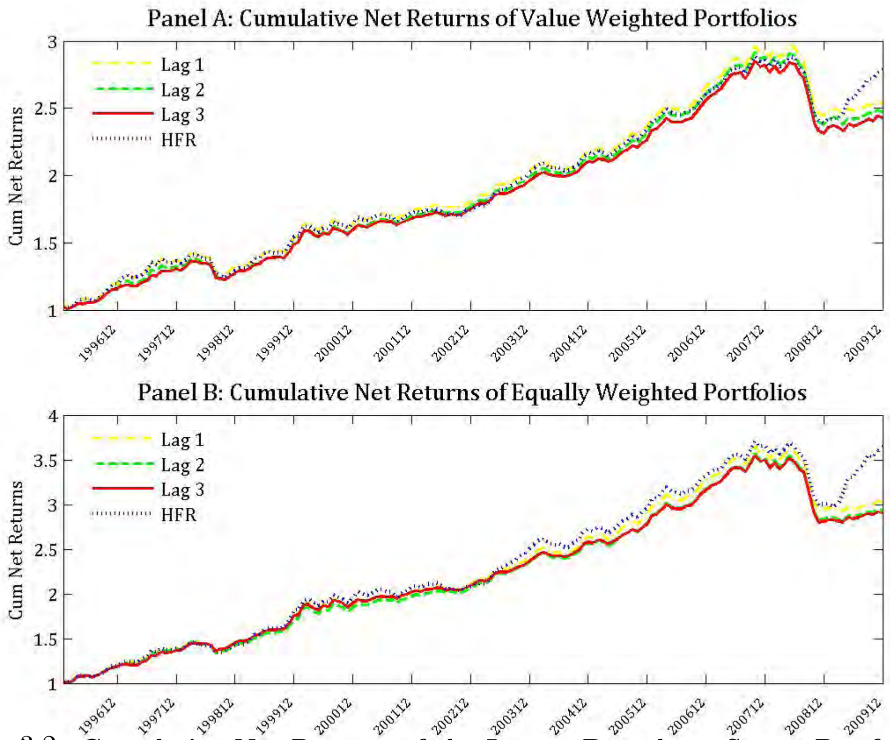

Figure 3.2: **Cumulative Net Returns of the Lowest Drawdown Status Portfolios (d = 1).** This figure presents the cumulative net returns of the lowest drawdown status portfolios. The sample period is January 1996-December 2009. See Table 3.2 for the description of portfolio formation.

In Figures 3.2 and 3.3 we plot the cumulative net returns of value weighted and equally weighted portfolios for lags 1, 2 and 3 for the lowest drawdown decile (Figure 3.2) and the highest drawdown decile (Figure 3.3). For comparison purposes, we also include the cumulative net return of the HFR portfolio in both figures. As we can observe in Figure 3.2, the cumulative returns of the lag 1, 2 and 3 portfolios are almost indistinguishable across lags, for both the equally and value weighted portfolios. Furthermore, the HFR portfolio tends to perform slightly better than the low drawdown portfolios, specially during the last year of the sample. In conclusion, in the case of the low drawdown status portfolios and performance measured in terms of cumulative returns: 1) there is no clear pattern of improvement or deterioration in performance as we increase the sorting lag, 2) all drawdown based portfolios perform worse than the HFR portfolio. The picture that arises from Figure 3.3 is completely different. In the case of the highest drawdown status portfolios and when performance is measured in

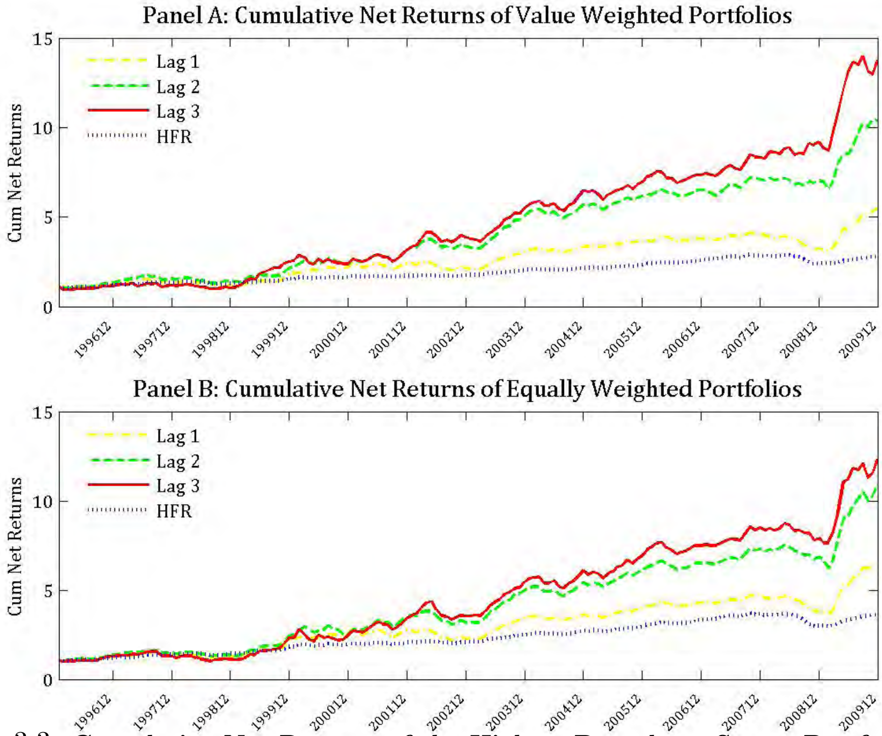

Figure 3.3: **Cumulative Net Returns of the Highest Drawdown Status Portfolios** ($d = 10$)**.** This figure presents the cumulative net returns of the highest drawdown status portfolios. The sample period is January 1996-December 2009. See Table 3.2 for the description of portfolio formation.

terms of cumulative returns: 1) performance improves as we increase the sorting lag, and 2) all drawdown based portfolios do much better than the HFR portfolio. Two more points are in order. First, the outperformance of the highest drawdown status relative to the lowest drawdown status portfolios is huge. For instance, \$1 invested in January 1996 in a low drawdown status portfolio results in a maximum portfolio value of 3.01\$ in December 2009 (investing in the one-lag equally weighted portfolio). On the other hand, \$1 invested during the same period in the high drawdown status portfolio results in maximal portfolio value of 13.71\$ (investing in the 3-lag value weighted portfolio). The final observation is that while equally weighted portfolios perform better than value weighted portfolios in the case of the lowest drawdown status portfolios, the opposite occurs in the case of the highest drawdown status portfolios. This means that while in the former case the relatively small funds in the portfolios are the best performers, in the later case the relatively larger funds are the best performers.

We now assess the performance of the portfolios in terms of risk adjusted net returns. Tables 3.3 and 3.4 report the estimation results of Fung and Hsieh (2004) seven-factor model for our 6 portfolios.[42] Table 3.3 reports the results for the lowest three and Table 3.4 for the highest three drawdown status portfolios. The tables corroborate that all the previous conclusions reached in terms of cumulative returns hold true in the case of risk adjusted returns. In particular, Table 3.3 shows that in the case of the lowest drawdown status portfolios: 1) alphas are almost constant across lags and only the one associated to the 3-lag portfolio is statistically significant at the standard significance levels, and 2) all drawdown based portfolios underperform the HFR portfolio. In the case of the highest drawdown status portfolios, Table 3.4 shows that: 1) all the alphas of the drawdown based portfolios are significant at the 1% level; 2) alphas are increasing in the lag; and, 3) all drawdown based portfolios outperform the HFR portfolio. It is important to notice that the outstanding performance of the largest drawdown portfolios is not only statistical but also economically significant. The alphas of the drawdown based portfolios are always more than double the alphas of the HFR portfolio. In the case of the value weighted 3-lag portfolio, it is more than 6 times larger! Finally, the improvement in performance as we increase the lag is also quantitatively important. For instance, in the case of value weighted portfolios alpha more than doubles, increasing from 0.64% in the one-lag portfolio to 1.23% in the 3-lag portfolio.

The previous results are remarkable for several reasons. First, the poor performance of the lowest drawdown portfolios relative to both the highest drawdown and the HFR portfolio is against the predictions of our benchmark economy and quite paradoxical when accounting for the main characteristics of the funds included in the sorts: their expensiveness and their success at raising capital (large inflows). More important, our results question the relationship between managers incentives (measured in terms of total delta) and performance proposed elsewhere. The funds in the lowest drawdown decile have the largest total delta, but they deliver the worst, rather than the best as the incentives theory suggests, relative performance! Of course, we must take this evidence with caution as the inferior performance could be explained by another hedge

[42] We thank David Hsieh for providing the risk factors on his web site: http://faculty.fuqua.duke.edu/ dah7/DataLibrary/TF-FAC.xls.

Table 3.3: **Risk-adjusted Performance of the Lowest Drawdown Status Portfolios** ($d = 1$)

This table reports OLS coefficient estimates when excess returns of the lowest drawdown status portfolios are regressed on Fung and Hsieh (2004) seven factors. The sample period is January 1996-December 2009. See Table 3.2 for the description of portfolio formation. Factors are described in the text. All return series are multiplied by 100 to make the intercepts in percentage form. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Intercept	0.13	0.13	0.12	0.18*	0.23**	0.22**	0.22**	0.34***
	(1.18)	(1.19)	(1.22)	(1.82)	(2.16)	(2.14)	(2.31)	(3.77)
SNP	0.18***	0.16***	0.15***	0.21***	0.22***	0.21***	0.20***	0.29***
	(5.22)	(5.12)	(5.09)	(7.05)	(7.12)	(7.22)	(7.34)	(11.75)
SizeSpr	0.13***	0.13***	0.14***	0.14***	0.19***	0.19***	0.18***	0.22***
	(2.86)	(2.77)	(3.11)	(4.03)	(4.06)	(4.23)	(4.22)	(6.54)
FXOpt	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01*
	(1.30)	(1.37)	(1.03)	(1.35)	(1.25)	(1.20)	(0.78)	(1.69)
ComOpt	0.01*	0.01*	0.01	0.01	0.02**	0.02*	0.01*	0.01*
	(1.83)	(1.67)	(1.41)	(1.59)	(2.19)	(1.93)	(1.84)	(1.75)
BdOpt	-0.02*	-0.02*	-0.02*	-0.02*	-0.01	-0.01	-0.01	-0.00
	(-1.78)	(-1.72)	(-1.67)	(-1.68)	(-1.19)	(-1.12)	(-0.93)	(-0.08)
Bd10Yr	0.09*	0.09*	0.08*	0.08*	0.10**	0.10**	0.09*	0.06
	(1.93)	(1.83)	(1.71)	(1.88)	(2.09)	(2.00)	(1.82)	(1.64)
CredSpr	0.13	0.15	0.14	0.17**	0.11	0.13	0.12	0.16**
	(1.41)	(1.62)	(1.64)	(2.47)	(1.14)	(1.39)	(1.32)	(2.38)
Adjusted R^2	41.8%	42.4%	44.3%	56.2%	49.9%	51.6%	51.6%	69.3%
Number of obs.	168	168	168	168	168	168	168	168

fund characteristic that affects negatively the performance of the funds in the lowest drawdown decile. This issue is further explored in Section 3.8. In any case, following

Table 3.4: **Risk-adjusted Performance of the Highest Drawdown Status Portfolios** ($d = 10$)

This table reports OLS coefficient estimates when excess returns of the highest drawdown status portfolios are regressed on Fung and Hsieh (2004) seven factors. The sample period is January 1996-December 2009. See Table 3.2 for the description of portfolio formation. Factors are described in the text. All return series are multiplied by 100 to make the intercepts in percentage form. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Intercept	0.64**	1.01***	1.23***	0.18*	0.80***	1.05***	1.10***	0.34***
	(2.48)	(3.89)	(3.35)	(1.82)	(3.40)	(4.13)	(3.32)	(3.77)
SNP	0.54***	0.59***	0.47***	0.21***	0.61***	0.60***	0.49***	0.29***
	(7.87)	(9.03)	(4.88)	(7.05)	(10.37)	(9.02)	(6.47)	(11.75)
SizeSpr	0.25***	0.38***	0.48***	0.14***	0.35***	0.46***	0.81***	0.22***
	(3.01)	(4.21)	(4.29)	(4.03)	(4.64)	(4.87)	(6.54)	(6.54)
FXOpt	0.01	0.02	0.03	0.01	0.02	0.02	0.03	0.01*
	(0.50)	(1.11)	(1.65)	(1.35)	(1.28)	(1.29)	(1.26)	(1.69)
ComOpt	-0.02	0.01	0.01	0.01	-0.01	0.01	0.00	0.01*
	(-1.04)	(0.42)	(0.55)	(1.59)	(-0.65)	(0.54)	(0.06)	(1.75)
BdOpt	0.01	0.02	0.02	-0.02*	0.04**	0.03	0.03	-0.00
	(0.68)	(1.01)	(0.60)	(-1.68)	(2.33)	(1.62)	(1.16)	(-0.08)
Bd10Yr	-0.08	-0.11	-0.12	0.08*	-0.15	-0.16	-0.06	0.06
	(-0.78)	(-0.91)	(-0.69)	(1.88)	(-1.57)	(-1.46)	(-0.47)	(1.64)
CredSpr	0.20	-0.11	0.01	0.17**	0.21	0.05	0.10	0.16**
	(1.20)	(-0.70)	(0.06)	(2.47)	(1.21)	(0.32)	(0.46)	(2.38)
Adjusted R^2	47.5%	44.6%	25.2%	56.2%	57.6%	53.1%	44.2%	69.3%
Number of obs.	168	168	168	168	168	168	168	168

the insights stated in Section 3.2, in the next section we explore some of the factors behind the poor performance of the lowest drawdown portfolios and conclude that the evidence points at the decile being heavily populated by insurance sellers who do not have skills to deliver outstanding performance. Hence, one view is that the presence of insurance sellers is (one of) the reason(s) behind the failure of the incentives hypothesis in our exercise. Strictly speaking, the incentives hypothesis does not apply to insurance sellers. However, these are funds that tend to have a large total delta. So, their heavy presence in the lowest drawdown decile distorts the relationship between incentives and performance, as for these funds we cannot expect superior performance (in spite of having high incentives when measured in terms of total delta). The second striking result is that, again contrary to what is expected in our benchmark economy, the increase in the lag when drawing from the largest drawdown decile results in an increase in performance. The evidence is, hence, in favor of the Darwinian selection process being in place. In the next section we also explore this result in more detail.

3.6 Dissecting the Performance of Drawdown Status Based Portfolios

In this section we explore in further detail the performance of our six portfolios to get a better understanding of the striking results obtained in Section 3.5. Our analysis provides evidence in favor of a heavy presence of insurance sellers in the lowest drawdown portfolios and corroborates the existence of a Darwinian selection mechanism operating among the large drawdown funds.

3.6.1 Assessing the Presence of Insurance Sellers: Performance in Times of Crises

In Section 3.2 we argued that one of the reason that can revert the predictions of the benchmark economy is the presence of low drawdown mimicking hedge funds. Among these we included the case of hedge funds pursuing insurance selling strategies. These funds are characterized by the implementation of strategies that perform well in normal market conditions, but suffer large loses in times of crisis. Hence, one way to spot their presence in the lowest drawdown portfolios consists on comparing the performance of the low drawdown portfolios in normal versus crisis times. To facilitate comparisons, we explore next the performance in normal versus times of crisis for both the lowest and highest drawdown status portfolios.

We assess performance in periods of crisis in two alternative ways. The first approach consists on directly computing the average returns of the portfolios in times of crisis. This approach provides a direct assessment of performance in terms of raw returns (returns not adjusted to risk). The second approach consists on computing the alphas in the context of the Fung and Hsieh (2004) seven-factor model including only the normal times in the analysis. The comparison of these alphas in normal times to the alphas associated to all times, which include the crisis periods, is also revealing of the performance of the portfolios during crisis, but this time in terms of risk-adjusted returns. Given that insurance sellers implement strategies that resemble the rolling over of short position on deep out of the money put options, we define crisis periods as those months in which we should expect the largest losses for these type of strategies. In the case of equity funds, these loses must be associated to very negative returns of the S&P index. They do not need to coincide with the month in which the the S&P falls, but perhaps the next few months. This is so because of two main reasons that reinforce each other. First, the fund manager may choose to hold on to the short position to avoid realizing loses in the crash month. Second, it may be the case that liquidity dries up in the options market during the crash month and managers may find it difficult to close the position. Given these considerations, we define "crisis" periods as the quarter that includes the month in which the S&P falls by more than 10% and the two months afterward. This criteria results in the following crisis quarters: August-October 1998, September-November 2002, October-December 2008 and February-April 2009. These periods coincide with well-known events: the first is related to the LTCM crisis; the second, to the "market confidence" crisis related to the Argentine default, accounting restatements after ENRON, terrorist threat to the US, etc.; the third, to the collapse of Lehman Brothers; and, the last to the further deterioration of the current financial crisis. Finally, we define as "normal" times the rest of months in our sample, January 1996-December 2009.

Table 3.5: **Performance in Normal Times and in Times of Crisis**

Panel A of this table reports the mean monthly raw returns of the portfolios during periods of crisis for the drawdown based portfolios. The periods of crisis are: August-October 1998, September-November 2002, October-December 2008, February-April 2009. Panel B reports OLS intercepts in percentage form when excess returns of drawdown based portfolios are regressed on Fung and Hsieh (2004) seven factors, excluding the periods of crisis. In explanation, the sample period is January 1996-December 2009; but excluding periods of crisis from the regression. See Table 3.2 for the description of portfolio formation. Factors are described in the text. Standard errors are white heteroscedasticity-consistent. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

Panel A: Performance in Times of Crisis (Mean Returns in %)

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Lowest DS Portfolios								
in times of crisis	-1.58	-1.58	-1.54	-1.37	-1.21	-1.29	-1.17	-0.72
in the whole period	0.57	0.55	0.54	0.63	0.68	0.66	0.65	0.79
Highest DS Portfolios								
in times of crisis	-0.54	1.59	2.87	-1.37	0.70	1.17	1.88	-0.72
in the whole period	1.11	1.49	1.71	0.63	1.24	1.53	1.65	0.79

Panel B: Performance in Normal Times (Regression Coefficients)

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Lowest DS Portfolios								
in normal times	0.27***	0.26***	0.26***	0.30***	0.33***	0.32***	0.32***	0.40***
in the whole period	0.13	0.13	0.12	0.18*	0.23**	0.22**	0.22**	0.34***
Highest DS Portfolios								
in normal times	0.68***	0.88***	1.03***	0.30***	0.72***	0.95***	0.92***	0.40***
in the whole period	0.64**	1.01***	1.23***	0.18*	0.80***	1.05***	1.10***	0.34***

In Table 3.5 we report the results of this exercise. Panel A of Table 3.5 reports the average raw net returns of the portfolios during periods of crisis for the equally and value weighted portfolios associated to the highest and lowest 3-lag drawdown status portfolios. As we can observe, during periods of crisis all the lowest drawdown status portfolios do worse than the HFR portfolio. While this is also true when looking at the whole sample (including both normal and crisis periods), the underperformance is much more pronounced in crisis periods. This result is specially strong in the case of equally weighted portfolios: while these portfolios only do marginally worse than the HFR portfolio in the whole sample, they have negative alphas in crisis periods that almost double in size the one of the HFR portfolio. For instance, the average monthly loss of 0.72% of the HFR portfolio is almost half the size of the average monthly loss of 1.29% associated to the 2-lag equally weighted lowest drawdown status portfolio. These results clearly point at a heavier presence of insurers in the lowest drawdown portfolios than in the whole HFR universe. They also suggest that insurers tend to be relatively small funds. On the other hand, the opposite picture arises when looking at the performance of the highest drawdown status portfolios. These portfolios not only do better than the HFR portfolio during crisis periods, but remarkably exhibit positive returns during these periods (in all but the one-lag value weighted portfolio). For instance, while the value weighted HFR portfolio suffers an average monthly *loss* of 1.37% during crisis periods, the 3-lag highest drawdown status portfolio yields and average *gain* of 2.87%. Furthermore, the overperformance relative to the HFR portfolio is much stronger in periods of crisis than during the whole period. These results suggest a very small presence, if not the complete absence, of insurers among the funds in the largest drawdown status portfolios.

Panel B of Table 3.5 reports the alphas and their levels of significance of the different portfolios in normal times, that is excluding the crisis periods. To facilitate the comparisons, we also include the alphas for the whole period (including crisis periods) reported in Tables 3.3 and 3.4. The results are truly remarkable and clearly reinforce all the conclusions inferred from the examination of Panel A. As we can observe, while the lowest drawdown status portfolios always do better, in terms of risk adjusted returns, in normal times than during the whole period, the opposite happens to the highest drawdown status portfolios, whose performance is much better in the whole period than in normal times (with the only exception of the one-lag value weighted portfolio). The first observation is, again, consistent with the heavy presence of insurers among the funds in the lowest drawdown status portfolios; the second is consistent with the absence of insurers in the highest drawdown status portfolios. Notice also that the comparison of alphas in normal times versus the whole period allows us to conjecture about risk adjusted returns in times of crisis. In particular, the results reported in Panel B suggest that while risk adjusted returns are negative for the lowest drawdown status portfolios in times of crisis, they are positive for the highest drawdown status portfolios in such periods. Hence, our conclusion on raw returns in times of crisis (Panel A) also apply to risk adjusted returns during these periods (Panel B).

In summary, the evidence reported in Table 3.5 is supportive of the following three important conclusions: 1) there is a heavy presence of insurance sellers among the funds in the lowest drawdown status portfolios, 2) insurance sellers are probably absent among the funds in the highest drawdown status portfolios; and 3) very remarkable, while the highest drawdown status portfolios perform extraordinarily well in times of crisis, both in terms of raw as well as risk adjusted returns, the opposite occurs to the lowest drawdown status portfolios.

3.6.2 Assessing the Stop Reporting and Darwinian Survival Processes

In Section 3.2 we argued that the predictions of the benchmark economy in terms of the sequential T-lags analysis could be reversed if the "stop reporting" and the "Darwinian selection" processes were very intense. In the previous section we did not find any patterns on the performance of the lowest drawdown portfolios as we increase the sorting lag. But we did find strong evidence consistent with the Darwinian selection process in the performance of the largest drawdown portfolios. In this subsection we explore these processes in more detail. A first approximation to this issue consist of computing the average number of consecutive years that a fund that stops reporting during the portfolio formation period stays in the $d = 1$ decile, and the average number of consecutive years that a fund that is liquidated during the portfolio formation period stays in the $d = 10$ decile. In Figure 3.4 we report the time series of these average times. Panel A of Figure 3.4 reveals that on average funds in the lowest drawdown decile that stop reporting during the portfolio formation period stay in the low drawdown decile for 3.09 consecutive years (that is, more than 3 years). This means that the *stop reporting* *process* cannot impose a clear bias in the relative performance of the lagged portfolios. In plain words, it cannot be the case that the lag 2 and 3 portfolios do better or worse than the lag 1 portfolio because the good funds that stop reporting are mechanically excluded from those portfolios. On the other hand, Panel B of Figure 3.4 reports that on average funds in the highest drawdown decile that liquidate in the portfolio formation period stay in the highest drawdown decile for 1.78 consecutive years (that is, less than 2 years). This number constitutes corroborating evidence for the *Darwinian selection hypothesis*. If we associate liquidating funds to funds managed by untalented traders, the fact that on average these funds survive in the highest drawdown decile for just 1.78 consecutive years imply that these funds will tend to be excluded from the portfolios as we increase the sorting lag from 1 to 3 years.

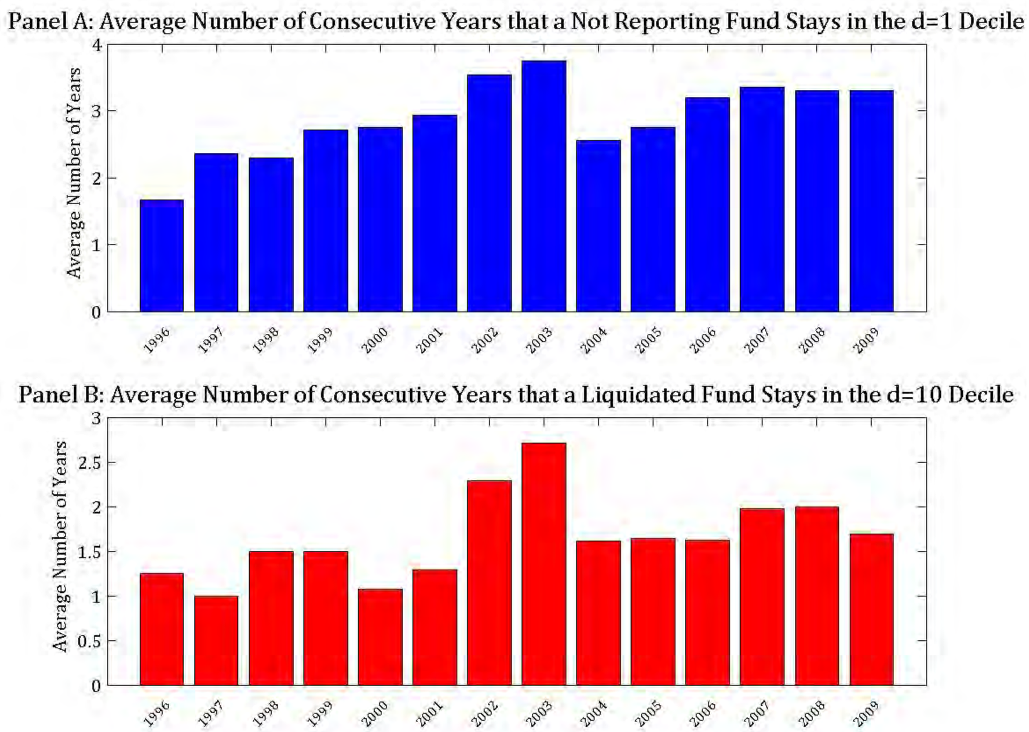

Figure 3.4: **Stop Reporting and Liquidation of Funds in the Portfolios.** Panel A of this figure presents the average number of consecutive years that a fund that stops reporting during the portfolio formation period stays in the $d = 1$ decile. Panel B of this figure presents the average number of consecutive years that a fund that is liquidated during the portfolio formation period stays in the $d = 10$ decile. The sample period is 1996-2009.

In summary, the statistics reported in Figure 3.4 corroborate that: 1) the stop reporting problem does not generate any explicit bias in the relative performance of the lowest drawdown portfolios as we increase the lag, and 2) the *Darwinian selection process* is, at least, one of the mechanisms that generates an improvement in the relative performance of the lowest drawdown portfolios as we increase the sorting lag.

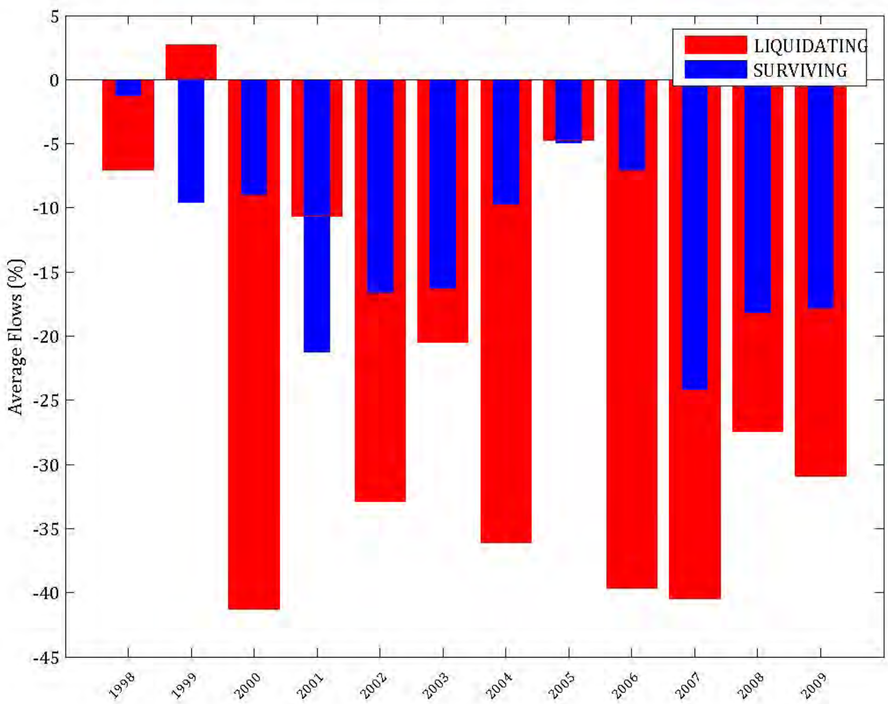

Figure 3.5: **Flows of Surviving vs. Liquidating Funds.** This figure plots the time series of the average 12-month lagged flows –excluding the flows of the liquidation month– of the portfolio of funds in the 3-lag highest drawdown decile (surviving funds) vs. the portfolio of funds in the 3-lag highest drawdown status portfolio that are liquidated (liquidating funds). There are no funds in the latter portfolio during 1996-1997. Hence, the sample period of comparison is 1998-2009.

From now until the rest of the section we concentrate on the Darwinian selection process. If the Darwinian selection mechanism is in place, then we should expect that funds that survive for several periods in the largest drawdown decile experience less outflows than funds that belong to the same decile but stop reporting. After all, according to the hypothesis, lag-3 high drawdown funds survive because (some) investors decide that it is best for them to stay than to exit and move to a new fund. We now test this prediction of the Darwinian selection hypothesis. In order not to contaminate the measurement of the flows of the liquidated funds with the flows of the liquidation month, we use 12-month lagged flows excluding the liquidation month. In Figure 3.5 we plot the time series of the 12-month lagged total flows to AUM of the portfolio of funds that survive in the lag-3 highest drawdown decile (surviving funds) versus the portfolio of funds in lag-3 highest decile that liquidate (liquidating funds). The figure clearly shows that surviving funds suffer much less outflows than liquidating funds. In particular, in all but three years the outflows associated to the portfolio of liquidating funds are much larger than the ones associated to surviving funds. In years such as 1998, 2000, 2002, 2004, 2006, 2008 and 2009 the differences in outflows are truly remarkable. This is clear evidence in favor of the Darwinian selection mechanism that adds to the one already reported in terms of outstanding performance of the high drawdown status portfolios.

Finally, we analyze managerial ownership as a final test of the Darwinian selection mechanism. In the Introduction we argued that funds in the highest drawdown status portfolio may survive because of management self-confidence rather than investors extended trust. If managerial self-confidence were the main driving force, then we should expect surviving funds to be (almost) fully owned by managers. In there we also argued that if this were the case we should expect talented managers to opt for closing the fund and start a new one. To clarify matters, we compute the time series of the the average managerial ownership of the funds in the 3-lag highest drawdown status portfolios. Managerial ownership is computed following Agarwal et al. (2009). The construction assumes that the manager starts the fund with zero ownership but from that point on reinvests in the fund all incentive fees collected over time. On the one hand, assuming a zero initial ownership may end up underestimating the true managerial stake in the fund; but, on the other hand, the assumption of full reinvestment of fees may result in an upward bias. In any case, the exercise is worthwhile undertaking. In Figure 3.6 we plot the time series of managerial ownership of the portfolio of funds in the 3-lag large drawdown status portfolio. As we can observe, the average managerial ownership is always below 25%; furthermore, at every point in time more than 80% of funds have a managerial ownership below 50%. These figures are clearly in favor of the Darwinian selection hypothesis as they corroborate that external investors in the fund opt to stay through hard times of large drawdowns.

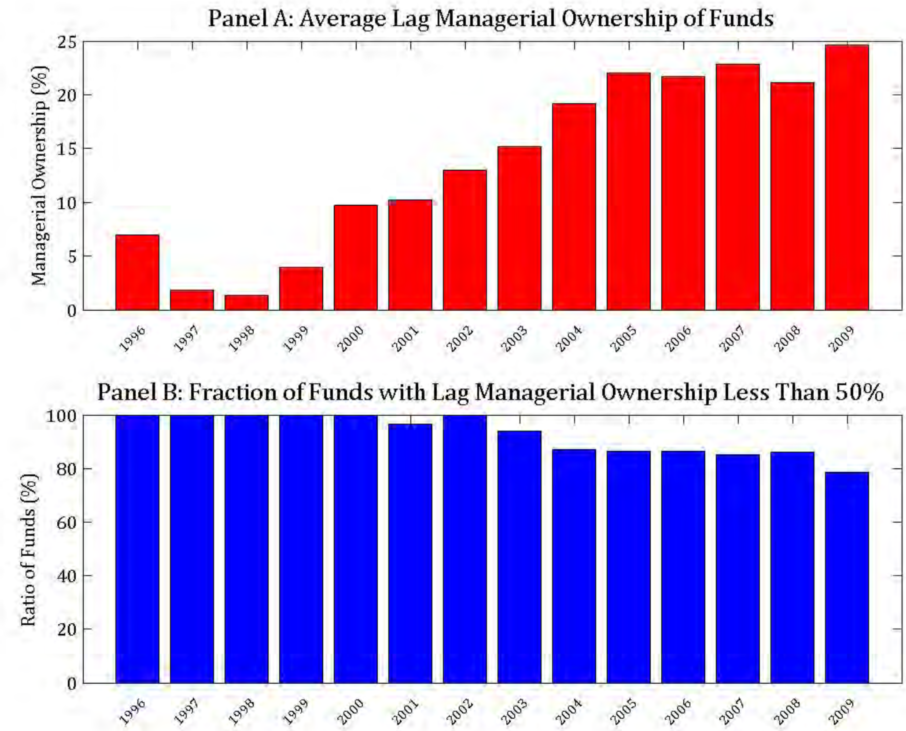

Figure 3.6: **Managerial Ownership in Surviving Funds.** Panel A of this figure plots the time series of managerial ownership of the portfolio of funds in the 3-lag high drawdown status portfolio. Panel B plots the fraction of funds in the 3-lag large drawdown status portfolio that have a managerial ownership below 50%. The sample period is 1996-2009.

3.7 Robustness Checks

In this subsection we explore in further detail the performance of our six drawdown based portfolios. First, we verify that our previous results also hold when analyzing the performance of the portfolios in terms of the funds' gross rather than net returns. Second, we establish robustness when controlling for economically relevant hedge fund characteristics. In particular we show that our results hold when controlling for the number of funds, size, style, and age of the funds in the portfolios. Third, we show the robustness of the results when making extreme assumptions on the returns of liquidated funds. Fourth, we investigate if the abnormal performance of the large drawdown funds is explained by liquidity risk bearing. Finally, we verify that the results are not driven by the well documented backfilling bias and that they survive when accounting for structural breaks.

3.7.1 Performance in Terms of Gross Returns

In the previous section we found that the lowest drawdown status portfolios underperform the highest drawdown status portfolios. This result was derived using the funds' net return as reported by hedge fund managers. Since net returns are returns net of fees, the result can be driven by the largest fees charged by the lowest drawdown status funds. In other words, it may be the case that the under performance of the lowest drawdown portfolios may vanish when we measure performance in terms of gross, rather than net, returns. In this subsection we redo the whole analysis of the previous section but using the funds' gross returns.

Gross returns are derived from net returns using the methodology in Agarwal et al. (2009). As explained in Section 4.2, each fund's gross returns are derived by tracking the entry/exit of investors in the funds according to the funds inflows/outflows and taking into account the individual high-water marks that apply to each investor in the fund to derive the fees charged by the fund manager. We believe the fees estimated with this methodology constitute the best possible proxy to the actual fees charged by the fund. Consequently, in our view, gross returns are computed using a sound methodology.

Tables 3.6 and 3.7 are the equivalent to Tables 3.3 and 3.4 when using hedge funds' gross returns, instead of the funds' net returns. According to Table 3.6, the performance of the low drawdown portfolios improves when measured in terms of gross returns, but still all alphas are smaller than the alpha of the HFR portfolio. Consequently, our previous result regarding the small drawdown portfolios remains valid. The outperformance of the large drawdown portfolios, both in isolation and when compared with the HFR portfolio, is confirmed in Table 3.7. All this means that: 1) the under-performance of the lowest drawdown status portfolios is not explained by the larger fees they charge to investors, and that 2) the over-performance, and the increasing performance in the lag, of the highest drawdown status portfolios are not driven by small fees. Hence, we conclude asserting that all the conclusions on performance obtained in Section 3.5 are robust to the type of returns used for performance evaluation.

Table 3.6: **Risk-adjusted Performance of the Lowest Drawdown Status Portfolios: Gross Returns**

This table reports OLS coefficient estimates when excess gross returns of the lowest drawdown status portfolios are regressed on Fung and Hsieh (2004) seven factors. The sample period is January 1996-December 2009. See Table 3.2 for the description of portfolio formation. Factors are described in the text. All return series are multiplied by 100 to make the intercepts in percentage form. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Intercept	0.31***	0.30***	0.29***	0.35***	0.43***	0.41***	0.41***	0.53***
	(2.75)	(2.80)	(2.88)	(3.43)	(3.99)	(3.99)	(4.20)	(5.71)
SNP	0.18***	0.17***	0.15***	0.21***	0.23***	0.21***	0.21***	0.29***
	(5.28)	(5.17)	(5.14)	(7.08)	(7.21)	(7.31)	(7.44)	(11.79)
SizeSpr	0.13***	0.13***	0.14***	0.14***	0.19***	0.19***	0.18***	0.22***
	(2.82)	(2.74)	(3.08)	(3.98)	(4.00)	(4.17)	(4.15)	(6.42)
FXOpt	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01
	(1.25)	(1.34)	(0.99)	(1.31)	(1.19)	(1.14)	(0.72)	(1.63)
ComOpt	0.01*	0.01*	0.01	0.01	0.02**	0.02**	0.01*	0.01*
	(1.88)	(1.72)	(1.45)	(1.64)	(2.28)	(2.01)	(1.91)	(1.82)
BdOpt	-0.02*	-0.02*	-0.02*	-0.02*	-0.01	-0.01	-0.01	-0.00
	(-1.76)	(-1.72)	(-1.67)	(-1.67)	(-1.09)	(-1.04)	(-0.85)	(-0.01)
Bd10Yr	0.09*	0.08*	0.07	0.07*	0.09*	0.09*	0.08*	0.06
	(1.80)	(1.73)	(1.60)	(1.75)	(1.90)	(1.82)	(1.65)	(1.45)
CredSpr	0.13	0.15	0.14	0.17**	0.10	0.13	0.12	0.16**
	(1.40)	(1.62)	(1.64)	(2.45)	(1.09)	(1.35)	(1.27)	(2.32)
Adjusted R^2	41.6%	42.3%	44.2%	55.9%	49.3%	51.0%	51.0%	68.7%
Number of obs.	168	168	168	168	168	168	168	168

Table 3.7: **Risk-adjusted Performance of the Highest Drawdown Status Portfolios: Gross Returns**

This table reports OLS coefficient estimates when excess gross returns of the highest drawdown status portfolios are regressed on Fung and Hsieh (2004) seven factors. The sample period is January 1996-December 2009. See Table 3.2 for the description of portfolio formation. Factors are described in the text. All return series are multiplied by 100 to make the intercepts in percentage form. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Intercept	0.76***	1.15***	1.43***	0.35***	0.94***	1.24***	1.32***	0.53***
	(2.93)	(4.42)	(3.73)	(3.43)	(3.96)	(4.80)	(3.92)	(5.71)
SNP	0.54***	0.59***	0.47***	0.21***	0.61***	0.60***	0.49***	0.29***
	(7.80)	(9.06)	(4.77)	(7.08)	(10.20)	(8.93)	(6.36)	(11.79)
SizeSpr	0.25***	0.38***	0.48***	0.14***	0.35***	0.46***	0.81***	0.22***
	(3.00)	(4.23)	(4.28)	(3.98)	(4.60)	(4.86)	(6.51)	(6.42)
FXOpt	0.01	0.02	0.03	0.01	0.02	0.02	0.03	0.01
	(0.49)	(1.11)	(1.61)	(1.31)	(1.26)	(1.24)	(1.21)	(1.63)
ComOpt	-0.02	0.01	0.01	0.01	-0.01	0.01	0.00	0.01*
	(-1.00)	(0.44)	(0.55)	(1.64)	(-0.61)	(0.60)	(0.13)	(1.82)
BdOpt	0.01	0.02	0.02	-0.02*	0.04**	0.03*	0.03	-0.00
	(0.69)	(1.05)	(0.67)	(-1.67)	(2.34)	(1.71)	(1.26)	(-0.01)
Bd10Yr	-0.08	-0.11	-0.12	0.07*	-0.15	-0.17	-0.08	0.06
	(-0.80)	(-0.91)	(-0.72)	(1.75)	(-1.60)	(-1.52)	(-0.58)	(1.45)
CredSpr	0.21	-0.11	0.03	0.17**	0.21	0.06	0.10	0.16**
	(1.23)	(-0.68)	(0.13)	(2.45)	(1.24)	(0.34)	(0.47)	(2.32)
Adjusted R^2	47.4%	44.6%	24.9%	55.9%	57.2%	52.6%	43.6%	68.7%
Number of obs.	168	168	168	168	168	168	168	168

3.7.2 Controlling for the number of funds in the portfolios and other hedge fund characteristics (size, age and strategy)

Table 3.2 reveals that the lowest and largest drawdown portfolios are very different in terms of the number of funds in the portfolios and in terms of some well-known characteristics that the literature has identified as related to performance. In this subsection we investigate whether our results in the previous section are explained by these factors.

A few remarks are in order before analyzing the role played by these factors in our analysis. First, notice that the different number of hedge funds included in the portfolios can not be the explanation of our results *per se*. This is obvious when observing that the lowest drawdown portfolios not only underperform the largest drawdown ones, but also the HFR portfolio, which is the largest portfolio in terms of number of funds. In any case, in the exercises that follow we do control for the number of funds in the portfolios. Second, regarding the role played by alternative characteristics on our results, as noticed in the introduction, the finding of a hedge fund characteristic that is very important in explaining our results would definitively tone down the value of drawdown status as a hedge fund characteristic, but would not challenge the value of drawdown status analysis.

Using the portfolio sorts methodology, in the previous subsection we obtained two main results. First, we found that largest drawdown status portfolios exhibit outstanding performance and that the performance is increasing in the sorting lag. Second, we showed that the highest drawdown status portfolios outperform the lowest drawdown status portfolios. One way to test if these results are explained by an alternative characteristic consists of checking for the robustness of the results to conditional sorting. For instance, in order to check if the results are driven by size, we would verify if the results still hold true for the sub-portfolios sorted by size within each of the drawdown status categories. One of the necessary conditions for this approach is the existence of enough funds and heterogeneity in terms of the new alternative characteristic in each of the drawdown status categories. Unfortunately this is not our case. First notice that the number of funds in the largest drawdown status portfolios ranges between 29 and 109. Any sub-portfolio of these according to some characteristic would necessarily result on a meaningless portfolio due to lack of diversification. On the other hand, regarding heterogeneity, consider for instance a characteristic such as total delta. Even if we had more funds in the largest drawdown status portfolios, so that a double sort on total delta could result in meaningful portfolios, we still would have a pool of hedge funds whose total delta is not comparable to the one of the lowest drawdown status portfolios. Hence a conditional sorts exercise is just not feasible in our case. Instead we rely on a weaker test that only addresses our second finding in the previous subsection, namely, that the largest drawdown status portfolios outperform the lowest drawdown status portfolios. For this reason, the results in this section should be taken together with those in Section 3.8 where we can better control for alternative hedge fund characteristics.

To analyze the role played by the number of funds in the portfolios and alternative characteristics on the superior performance of the largest drawdown portfolios we compare the performance of the largest drawdown portfolios to matching portfolios in number of funds, size, strategy and age drawn from the lowest drawdown decile.[43] More specifically, we proceed as follows. First, at the end of each period t, for each lag T we sort all funds in the lowest drawdown set, $DS_{1,t}(T)$, in size quintiles and age terciles. Second, for each fund in the largest drawdown portfolio, $DS_{10,t}(T)$, we randomly draw a matching hedge fund from the corresponding $DS_{1,t}(T)$ with the same strategy and in the intersection of the quantiles to which the hedge fund characteristics belong to. For instance, suppose a fund has the following characteristics: it has \$500 million of AUM, it is an event driven fund and it is 6 years old. Then the matching fund is an event driven fund randomly chosen from those funds in the intersection of the size quintile that includes \$500 million and the age tercile that includes 6 years. We then compute the returns of this matching control portfolio, and compare its performance to the corresponding largest drawdown portfolio. Table 3.8 reports the performance of the matching portfolios. Comparing Table 3.8 and Table 3.3 we verify an overall improvement in the performance of the small drawdown portfolios when funds are sorted according to the characteristics of the large drawdown portfolios (matching portfolios). In the case of

[43]Table 3.2 also shows that the lowest and largest drawdown portfolios are very different in terms of total delta. Unfortunately, we have not been able to control for this characteristic in our exercise as reasonable matching funds in terms of this characteristic do not exist in the lowest drawdown portfolios.

value weighted portfolios, the 3-lag portfolio now exhibits a significant alpha, which is larger than the alpha of the HFR portfolio; in the case of the equally weighted portfolios, all alphas remain significant but now are in line with the alpha of HFR, while before they were much lower. But, although performance improves, it still is short to explain the out-performance of the large drawdown portfolios. In particular, comparing Table 3.8 and Table 3.4, we see that the alphas of the large drawdown portfolios are close to three times bigger than the alpha of the matching portfolios. This means that the characteristics included in the present exercise only explain a small fraction of the outstanding performance of the high drawdown status portfolios. Hence, we conclude that drawdown status is a hedge fund characteristic that predicts future performance both unconditionally and when controlling for the relevant characteristics.

3.7.3 De-reporting Returns

Hedge funds stop reporting to databases for two very different reasons: success and death. *Ex ante* we should expect that the first reason is more relevant for the lowest and the second for the highest drawdown status portfolios. If this is the case, then it could be possible that the difference in performance of these two portfolios arises because we are not properly accounting for the actual returns of hedge funds when they stop reporting. Fortunately, HFR classify dead funds into the "not reporting" and "liquidated" categories.[44] Hence we can make suitable assumptions on the de-reporting returns that apply to each of these cases in order to verify if our results are driven by this phenomena. This is the approach we adopt in this subsection.

Regarding liquidated funds, following Posthuma and van der Sluis (2003) we add an extra -50% return in their last month of reporting. This is extremely conservative as inferred from the analysis of Ackermann et al (1999), Fung and Hsieh (2006) and Hodder et al. (2008). Regarding the de-reporting return for funds that stop reporting (but are

[44] In the previous versions of HFR database, the information on whether a fund is "not reporting" or "liquidated" was missing for some funds and the fund was classified as "liquidated/no longer reporting". Hence some papers had developed diagnosis to classify funds into "not reporting" and "liquidated" categories. See for instance, Fung et al. (2008). But in our recent version of HFR database, this information is available for all funds, hence we do not need further diagnosis.

Table 3.8: **Performance Controlling for Size, Age, Strategy and the Number of Funds**

This table reports OLS coefficient estimates when excess returns of the matching portfolios are regressed on Fung and Hsieh (2004) seven factors. The sample period is January 1996-December 2009. Matching portfolios are created as follows. First, at the end of each period t, we sort all funds in the lowest drawdown set, into quintiles according to size and into terciles according to age. Second, for each fund in the largest decile portfolio, we randomly draw a matching hedge fund from the lowest decile portfolio with the same strategy and in the intersection of the corresponding quantiles in which hedge fund characteristics belong to. Factors are described in the text. All return series are multiplied by 100 to make the intercepts in percentage form. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Intercept	0.26	0.24	0.48**	0.18*	0.34***	0.31**	0.34*	0.34***
	(1.45)	(1.36)	(2.10)	(1.82)	(2.67)	(2.34)	(1.75)	(3.77)
SNP	0.26***	0.30***	0.37***	0.21***	0.32***	0.34***	0.45***	0.29***
	(4.95)	(5.85)	(5.73)	(7.05)	(8.29)	(7.69)	(7.48)	(11.75)
SizeSpr	0.26***	0.27***	0.14**	0.14***	0.23***	0.30***	0.19***	0.22***
	(5.24)	(3.52)	(2.02)	(4.03)	(5.11)	(5.39)	(3.20)	(6.54)
FXOpt	0.02**	0.01	0.02	0.01	0.01*	0.01*	0.00	0.01*
	(2.47)	(0.84)	(1.32)	(1.35)	(1.75)	(1.87)	(0.37)	(1.69)
ComOpt	-0.00	0.03**	0.02	0.01	0.00	0.01	0.02	0.01*
	(-0.36)	(2.53)	(1.33)	(1.59)	(0.24)	(1.17)	(1.29)	(1.75)
BdOpt	-0.03	-0.01	-0.02	-0.02*	-0.01	-0.01	-0.02	-0.00
	(-1.29)	(-0.94)	(-0.81)	(-1.68)	(-0.74)	(-0.82)	(-0.89)	(-0.08)
Bd10Yr	0.08	0.17**	0.08	0.08*	0.07	0.06	0.02	0.06
	(1.49)	(2.45)	(1.01)	(1.88)	(1.31)	(1.38)	(0.31)	(1.64)
CredSpr	0.05	0.13	0.03	0.17**	0.08	-0.03	-0.03	0.16**
	(0.51)	(1.02)	(0.22)	(2.47)	(0.90)	(-0.31)	(-0.27)	(2.38)
Adjusted R^2	41.3%	39.4%	31.8%	56.2%	55.4%	54.9%	46.3%	69.3%
Number of obs.	168	168	168	168	168	168	168	168

not liquidated), there is not much we can do. It is true that investors in these funds probably will continue enjoying large returns, but any assumption regarding this in our analysis would be arbitrary. So, for these funds we just keep the last return provided by the manager as we did before. Tables 3.9 and 3.10 report the equivalent results to Tables 3.3 and 3.4, but when using the previous criteria for the returns of liquidated funds.

The comparison of Table 3.9 (correcting liquidated fund returns) and Table 3.3 (without correction) reveals that the correction severely reduces the performance of the portfolios, which implies either a heavy presence of liquidated funds in the low drawdown status portfolios or that the correction is too strong to take it seriously. Under the correction, none of the portfolios exhibit statistically significant alphas. If we ignore the lack of statistical significance, we can observe that the main qualitative properties of Table 3.3 remain true in Table 3.9, namely: all the drawdown based portfolios underperform the HFR portfolio and there is no improvement nor deterioration in performance as we increase the sorting lag. The comparison of Tables 3.10 and 3.4 also reveals a heavy presence of liquidated funds in the high drawdown status portfolios or that the correction imposed in returns is too strong. Unlike in the previous case, all alphas remain larger than the alpha of the HFR portfolio (which is not statistically significant) and all, but the one-lag portfolio, exhibit statistically significant alphas. In particular, the 3-lag value weighted portfolio has an alpha of 0.99% which is statistically significant at the 99% confidence level and almost 10 times bigger than the alpha of the HFR portfolio (not significant). Hence, we observe that Table 3.10 delivers the same qualitative results as Table 3.4, namely: all the drawdown based portfolios outperform the HFR portfolio (with the single exception of the one-lag portfolios) and performance increases as we increase the sorting lag. In summary, our results in Section 3.5 are not challenged at all when correcting returns to account for funds liquidation using, perhaps, a too strong criteria. Hence, the different returns of the low versus high drawdown status portfolios cannot be explained by the returns of liquidated funds.

Finally, we perform a sensitivity analysis on the choice of the liquidation return. As Table 3.11 demonstrates, both of the 3-lag highest drawdown portfolios preserve

Table 3.9: **Risk-adjusted Performance of the Lowest Drawdown Status Portfolios: Liquidated Funds Returns**

This table reports OLS coefficient estimates when excess returns of the lowest drawdown status portfolios are regressed on Fung and Hsieh (2004) seven factors after correcting for liquidated funds returns. Returns are corrected in the sense that for the funds that are liquidated, we respectively add an extra negative return of 50% in their last month of reporting. The sample period is January 1996-December 2009. See Table 3.2 for the description of portfolio formation. Factors are described in the text. All return series are multiplied by 100 to make the intercepts in percentage form. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Intercept	0.07	0.07	0.06	0.10	0.05	0.04	0.04	0.11
	(0.65)	(0.62)	(0.63)	(1.03)	(0.44)	(0.35)	(0.43)	(1.17)
SNP	0.18***	0.17***	0.16***	0.21***	0.23***	0.22***	0.21***	0.29***
	(5.51)	(5.46)	(5.51)	(7.23)	(7.06)	(7.19)	(7.34)	(11.83)
SizeSpr	0.13***	0.13***	0.14***	0.14***	0.18***	0.19***	0.18***	0.21***
	(2.82)	(2.74)	(3.08)	(3.80)	(3.73)	(3.96)	(3.95)	(5.96)
FXOpt	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01
	(1.18)	(1.26)	(0.91)	(1.25)	(0.92)	(0.87)	(0.48)	(1.27)
ComOpt	0.01*	0.01*	0.01	0.01	0.02**	0.02*	0.02*	0.01*
	(1.83)	(1.67)	(1.42)	(1.57)	(2.17)	(1.92)	(1.86)	(1.74)
BdOpt	-0.02*	-0.02*	-0.02*	-0.02*	-0.01	-0.01	-0.01	-0.00
	(-1.94)	(-1.91)	(-1.89)	(-1.80)	(-1.41)	(-1.46)	(-1.32)	(-0.23)
Bd10Yr	0.09*	0.08	0.08	0.07	0.10*	0.10*	0.09	0.06
	(1.73)	(1.63)	(1.51)	(1.63)	(1.76)	(1.73)	(1.54)	(1.24)
CredSpr	0.12	0.13	0.13	0.16**	0.10	0.12	0.11	0.15**
	(1.29)	(1.49)	(1.49)	(2.28)	(0.96)	(1.19)	(1.08)	(2.00)
Adjusted R^2	41.5%	42.2%	44.0%	55.2%	47.3%	49.4%	49.1%	67.3%
Number of obs.	168	168	168	168	168	168	168	168

Table 3.10: **Risk-adjusted Performance of the Highest Drawdown Status Portfolios: Liquidated Funds Returns**

This table reports OLS coefficient estimates when excess returns of the highest drawdown status portfolios are regressed on Fung and Hsieh (2004) seven factors after correcting for liquidated funds returns. Returns are corrected in the sense that for the funds that are liquidated, we respectively add an extra negative return of 50% in their last month of reporting. The sample period is January 1996-December 2009. See Table 3.2 for the description of portfolio formation. Factors are described in the text. All return series are multiplied by 100 to make the intercepts in percentage form. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Intercept	0.27	0.56*	0.99***	0.10	0.33	0.66**	0.73**	0.11
	(1.02)	(1.87)	(2.69)	(1.03)	(1.42)	(2.55)	(2.16)	(1.17)
SNP	0.57***	0.64***	0.48***	0.21***	0.63***	0.60***	0.52***	0.29***
	(8.24)	(6.99)	(4.94)	(7.23)	(11.06)	(8.59)	(6.79)	(11.83)
SizeSpr	0.24***	0.39***	0.49***	0.14***	0.35***	0.46***	0.81***	0.21***
	(2.81)	(4.30)	(4.39)	(3.80)	(4.62)	(4.69)	(6.28)	(5.96)
FXOpt	0.01	0.01	0.02	0.01	0.02	0.02	0.02	0.01
	(0.50)	(0.96)	(1.07)	(1.25)	(1.01)	(1.28)	(0.86)	(1.27)
ComOpt	-0.01	0.01	0.01	0.01	-0.01	0.01	-0.00	0.01*
	(-0.89)	(0.48)	(0.66)	(1.57)	(-0.53)	(0.41)	(-0.02)	(1.74)
BdOpt	0.01	0.03	0.02	-0.02*	0.04**	0.03*	0.03	-0.00
	(0.51)	(1.42)	(0.80)	(-1.80)	(2.08)	(1.83)	(1.22)	(-0.23)
Bd10Yr	-0.07	-0.09	-0.05	0.07	-0.16	-0.15	-0.06	0.06
	(-0.66)	(-0.73)	(-0.29)	(1.63)	(-1.59)	(-1.29)	(-0.40)	(1.24)
CredSpr	0.23	-0.05	0.13	0.16**	0.21	0.13	0.13	0.15**
	(1.34)	(-0.32)	(0.62)	(2.28)	(1.25)	(0.85)	(0.62)	(2.00)
Adjusted R^2	48.0%	41.3%	28.4%	55.2%	59.3%	53.8%	44.8%	67.3%
Number of obs.	168	168	168	168	168	168	168	168

their high and significantly positive alphas even if we assume that liquidation return is -70%. Moreover, value weighted portfolios have a significant alpha at all levels of liquidation return. On the contrary, lowest drawdown status portfolios, along with the HFR portfolio, do not have significant alphas at any level. Moreover, equally weighted portfolios have negative alphas, although insignificant.

3.7.4 Controlling for Liquidity

Funds that specialize in illiquid investments often impose long lockup and restriction periods. These funds are less liquid and investors in the fund require an extra return for the lack of liquidity. This observation suggests that one of the possible reasons behind the outstanding performance of our large drawdown portfolios is that they just compensate investors for bearing a large liquidity risk. If this were the case, we would also have a problem with our Darwinian selection hypothesis as this requires enough liquidity so that investors can exit from the unfitted funds, funds managed by untalented traders. Hence, analyzing liquidity plays a dual role because it entails a liquidity premium and affects investors discretionality. Verifying that our results survive the liquidity test is a must.

There are two approaches to liquidity in hedge fund management: the analysis of lockup and restriction periods, and the addition of a liquidity factor in the Fung and Hsieh (2004) model.[45] Regarding lockup and restriction periods, Table 3.2 of Section 3.5 already revealed that these cannot be the explanation of the outstanding performance of the large drawdown portfolios relative to the low drawdown portfolios, as the average lockup and restriction periods are almost identical across the board. Although this is perhaps sufficient to disregard liquidity considerations, we further analyze the issue in the context of our portfolio sorts methodology. Following Ramadorai (2012), for each fund we define the variable *withdrawal restriction* as the sum of the fund's lockup and restriction periods. Then we analyze the performance of our drawdown based portfolios when restricted to include only funds that satisfy some criteria in terms of the withdrawal

[45]See, for instance, Gibson and Wang (2010) and Aragon (2007).

Table 3.11: **Liquidated Funds Returns: Sensitivity Analysis**

This table reports OLS intercepts in percentage form when excess returns of the drawdown status portfolios are regressed on Fung and Hsieh (2004) seven factors after correcting for liquidated funds returns. Returns are corrected as such: For the funds that are liquidated, we respectively add an extra negative return in their last month of reporting. For brevity, results are reported for negative returns of 50%, 60%, 70%, 80%, 90% and 100%. The sample period is January 1996-December 2009. See Table 3.2 for the description of portfolio formation. Factors are described in the text. Standard errors are white heteroscedasticity-consistent. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
				Lowest DS Portfolios				
Liquidation Return								
-50%	0.07	0.07	0.06	0.10	0.05	0.04	0.04	0.11
-60%	0.06	0.05	0.05	0.09	0.01	0.00	0.01	0.06
-70%	0.05	0.04	0.04	0.07	-0.02	-0.03	-0.03	0.02
-80%	0.04	0.03	0.03	0.06	-0.06	-0.07	-0.06	-0.03
-90%	0.03	0.02	0.02	0.04	-0.09	-0.10	-0.10	-0.07
-100%	0.02	0.01	0.01	0.03	-0.12	-0.14	-0.13	-0.12
				Highest DS Portfolios				
Liquidation Return								
-50%	0.27	0.56*	0.99***	0.10	0.33	0.66**	0.73**	0.11
-60%	0.20	0.47	0.95**	0.09	0.24	0.58**	0.65*	0.06
-70%	0.12	0.38	0.90**	0.07	0.14	0.50*	0.58*	0.02
-80%	0.05	0.29	0.86**	0.06	0.05	0.42	0.51	-0.03
-90%	-0.02	0.20	0.81**	0.04	-0.03	0.35	0.44	-0.07
-100%	-0.08	0.10	0.74*	0.03	-0.12	0.25	0.32	-0.12

restriction variable. In particular, we analyze the performance of portfolios of funds for the following three cases: restriction period smaller than 3, smaller than 2 and smaller than 1 year. Table 3.12 reports the results of this exercise. To simplify the exposition, we only report results for the value weighted portfolios. As we can see in the table, the restricted portfolios exhibit the same features as the unrestricted ones, namely, significant risk adjusted returns in the case of the high drawdown portfolios and no outstanding performance in the case of the low drawdown status portfolios.

We now proceed to asses the role played by liquidity on our results in terms of the liquidity factor. Given that we already use a transformed version of the Fung and Hsieh (2004) factors to account for tradability, we obtain the traded liquidity factor described in Pastor and Stambaugh (2003).[46] We multiply this series by negative one, so that a positive shock in the factor can be interpreted as an improvement in liquidity. In Tables 3.13 and we report the performance of our drawdown based portfolios when this liquidity factor is added to the Fung and Hsieh (2004) seven factors. Table 3.13 reveals that, like the HFR portfolio, all low drawdown portfolios load positive and significantly to the liquidity factor. Also, the addition of the liquidity factor reduces the (non-significant) alphas by more than 50%. The impact of the liquidity factor on the large drawdown portfolios is very different. Table reveals that none of the large drawdown portfolios has statistically significant loads to the liquidity factor and that the alphas are not affected by the introduction of the new factor. Hence, we can conclude that none of the results obtained in this paper are driven by liquidity considerations.

3.7.5 Controlling for the Backfilling Bias

It is well known that hedge funds typically undergo an incubation period to build a good track record. Then the manager enters the fund into databases to attract new investors. The incubation period performance is backfilled at the entry date, what generates a clear bias in hedge fund performance as it is reported in databases. In order

[46] We thank Lubos Pastor and Robert Stambaugh for providing the liquidity factors on their web sites: http://faculty.chicagobooth.edu/lubos.pastor/research/liq_data_1962_2008.txt and http://finance.wharton.upenn.edu/~stambaugh/liq_data_1962_2010.txt, respectively.

Table 3.12: **Controlling for Withdrawal Restriction Periods**

This table reports OLS coefficient estimates when excess returns of the drawdown based portfolios are regressed on Fung and Hsieh (2004) seven factors after controlling for withdrawal restriction periods. For brevity, 3-lag value-weighted portfolio results are reported. The funds that have withdrawal restriction periods longer than 1, 2 or 3 years are eliminated from the sample, in respective studies. *Withdrawal restriction period* is given by the sum of the *lockup period* and *restriction period*. The sample period is January 1996-December 2009. See Table 3.2 for the description of portfolio formation. Factors are described in the text. All return series are multiplied by 100 to make the intercepts in percentage form. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Low Drawdown Portfolio			**High Drawdown Portfolio**			**HFR Portfolio**		
	1 Year	2 Years	3 Years	1 Year	2 Years	3 Years	1 Year	2 Years	3 Years
Intercept	0.08	0.06	0.12	1.17***	1.23***	1.22***	0.14	0.14	0.18*
	(0.80)	(0.58)	(1.25)	(2.85)	(3.23)	(3.23)	(1.35)	(1.36)	(1.82)
SNP	0.12***	0.15***	0.15***	0.33***	0.47***	0.48***	0.17***	0.21***	0.21***
	(4.21)	(4.96)	(5.09)	(3.23)	(4.85)	(4.88)	(5.86)	(6.86)	(7.04)
SizeSpr	0.11***	0.13***	0.14***	0.27***	0.47***	0.48***	0.12***	0.14***	0.14***
	(2.80)	(2.90)	(3.07)	(2.59)	(4.24)	(4.29)	(3.61)	(4.02)	(3.99)
FXOpt	0.01	0.01	0.01	0.04*	0.03	0.04	0.01	0.01	0.01
	(1.23)	(1.07)	(1.06)	(1.78)	(1.65)	(1.67)	(1.57)	(1.39)	(1.37)
ComOpt	0.01	0.01	0.01	0.03	0.01	0.01	0.01*	0.01	0.01
	(1.54)	(1.49)	(1.42)	(1.03)	(0.45)	(0.53)	(1.72)	(1.57)	(1.58)
BdOpt	-0.01	-0.01	-0.02	0.02	0.02	0.02	-0.01	-0.02	-0.02
	(-1.30)	(-1.61)	(-1.67)	(0.72)	(0.69)	(0.66)	(-1.31)	(-1.60)	(-1.67)
Bd10Yr	0.10**	0.09*	0.08*	-0.22	-0.11	-0.12	0.09**	0.08*	0.08*
	(2.14)	(1.82)	(1.70)	(-1.04)	(-0.61)	(-0.70)	(2.19)	(1.95)	(1.86)
CredSpr	0.15*	0.15	0.14	-0.09	0.04	0.02	0.17**	0.17**	0.17**
	(1.74)	(1.63)	(1.63)	(-0.34)	(0.15)	(0.09)	(2.54)	(2.49)	(2.47)
Adjusted R^2	34.0%	41.8%	44.2%	10.4%	25.2%	25.4%	44.4%	54.1%	56.0%
Number of obs.	168	168	168	168	168	168	168	168	168

Table 3.13: **Risk-adjusted Performance of the Lowest Drawdown Status Portfolios: Controlling for the Liquidity Factor**

This table reports OLS coefficient estimates when excess returns of the lowest drawdown status portfolios are regressed on Fung and Hsieh (2004) seven factors and liquidity factor. Liquidity factor is the traded liquidity factor series from the study of Pastor and Stambaugh (2003), multiplied by negative one so that a positive shock can be interpreted as an improvement to market liquidity. The sample period is January 1996-December 2009. See Table 3.2 for the description of portfolio formation. Factors are described in the text. All return series are multiplied by 100 to make the intercepts in percentage form. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Intercept	0.06	0.06	0.06	0.14	0.16	0.15	0.16	0.31***
	(0.52)	(0.53)	(0.55)	(1.33)	(1.38)	(1.38)	(1.54)	(3.24)
SNP	0.18***	0.17***	0.16***	0.21***	0.23***	0.22***	0.21**	0.29***
	(6.26)	(6.09)	(6.08)	(7.84)	(8.63)	(8.56)	(8.73)	(12.97)
SizeSpr	0.14***	0.13***	0.14***	0.15***	0.19***	0.20***	0.19***	0.22***
	(3.23)	(3.10)	(3.47)	(4.39)	(4.50)	(4.64)	(4.63)	(6.89)
FXOpt	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01*
	(1.53)	(1.60)	(1.28)	(1.49)	(1.48)	(1.41)	(1.00)	(1.79)
ComOpt	0.01*	0.01*	0.01	0.01*	0.02**	0.02**	0.01*	0.01*
	(1.94)	(1.80)	(1.54)	(1.66)	(2.28)	(2.03)	(1.92)	(1.79)
BdOpt	-0.02*	-0.02*	-0.02*	-0.02*	-0.01	-0.01	-0.01	-0.00
	(-1.95)	(-1.87)	(-1.82)	(-1.79)	(-1.41)	(-1.31)	(-1.14)	(-0.20)
Bd10Yr	0.10**	0.09**	0.08*	0.08**	0.11**	0.10**	0.09**	0.07*
	(2.13)	(2.02)	(1.89)	(2.02)	(2.27)	(2.15)	(1.96)	(1.74)
CredSpr	0.09	0.11	0.11	0.14**	0.07	0.09	0.09	0.14**
	(1.03)	(1.28)	(1.30)	(2.20)	(0.77)	(1.06)	(1.01)	(2.13)
Liquidity	-0.07**	-0.06**	-0.06**	-0.05*	-0.07**	-0.06**	-0.06*	-0.04
	(-2.16)	(-2.07)	(-2.06)	(-1.79)	(-2.16)	(-2.01)	(-1.94)	(-1.52)
Adjusted R^2	44.0%	44.3%	46.3%	56.9%	51.6%	53.0%	52.9%	69.6%
Number of obs.	168	168	168	168	168	168	168	168

Table 3.14: **Risk-adjusted Performance of the Highest Drawdown Status Portfolios: Controlling for the Liquidity Factor**

This table reports OLS coefficient estimates when excess returns of the highest drawdown status portfolios are regressed on Fung and Hsieh (2004) seven factors and liquidity factor. Liquidity factor is the traded liquidity factor series from the study of Pastor and Stambaugh (2003), multiplied by negative one so that a positive shock can be interpreted as an improvement to market liquidity. The sample period is January 1996-December 2009. See Table 3.2 for the description of portfolio formation. Factors are described in the text. All return series are multiplied by 100 to make the intercepts in percentage form. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Intercept	0.65**	0.96***	1.24***	0.14	0.81***	1.03***	1.05***	0.31***
	(2.46)	(3.56)	(3.09)	(1.33)	(3.19)	(3.75)	(2.98)	(3.24)
SNP	0.54***	0.60***	0.47***	0.21***	0.60***	0.60***	0.50***	0.29***
	(7.75)	(9.15)	(4.81)	(7.84)	(10.39)	(8.89)	(6.44)	(12.97)
SizeSpr	0.25***	0.38***	0.48***	0.15***	0.35***	0.47***	0.81***	0.22***
	(2.98)	(4.26)	(4.21)	(4.39)	(4.61)	(4.87)	(6.58)	(6.89)
FXOpt	0.01	0.02	0.03*	0.01	0.02	0.02	0.03	0.01*
	(0.49)	(1.18)	(1.65)	(1.49)	(1.30)	(1.33)	(1.32)	(1.79)
ComOpt	-0.02	0.01	0.01	0.01*	-0.01	0.01	0.00	0.01*
	(-1.05)	(0.46)	(0.55)	(1.66)	(-0.65)	(0.56)	(0.09)	(1.79)
BdOpt	0.01	0.02	0.02	-0.02*	0.04**	0.03	0.03	-0.00
	(0.69)	(0.97)	(0.61)	(-1.79)	(2.31)	(1.58)	(1.08)	(-0.20)
Bd10Yr	-0.08	-0.11	-0.12	0.08**	-0.15	-0.16	-0.06	0.07*
	(-0.78)	(-0.87)	(-0.69)	(2.02)	(-1.55)	(-1.42)	(-0.43)	(1.74)
CredSpr	0.21	-0.14	0.02	0.14**	0.21	0.04	0.07	0.14**
	(1.16)	(-0.86)	(0.09)	(2.20)	(1.19)	(0.23)	(0.30)	(2.13)
Liquidity	0.01	-0.04	0.01	-0.05*	0.01	-0.02	-0.05	-0.04
	(0.21)	(-0.61)	(0.12)	(-1.79)	(0.12)	(-0.28)	(-0.60)	(-1.52)
Adjusted R^2	47.2%	44.4%	24.8%	56.9%	57.3%	52.8%	44.0%	69.6%
Number of obs.	168	168	168	168	168	168	168	168

to correct the bias some of the early history of hedge funds performance must be disregarded. In general, researchers eliminate from one to two of the first years of data of hedge funds. We take a conservative approach in the present robustness check and eliminate the first two years. Tables 3.15 and 3.16 report the performance of our drawdown portfolios. Again all of our previous results remain true. Indeed, the results improve qualitatively as in this case, while the HFR portfolio stops exhibiting outstanding performance, our large drawdown based portfolios continue exhibiting positive and significant alphas.

3.7.6 Structural Breaks Analysis

In this section we perform a structural breaks analysis for our drawdown based portfolios along with the HFR portfolio. The significance of structural breaks in hedge fund return series was first suggested by the study of Fung and Hsieh (2004), where they use HFR Funds of Funds index returns for the period January 1994-December 2002 to proxy for a typical hedge fund portfolio. They identify two structural breaks: September 1998, which they attribute to the LTCM debacle, and March 2000, which they attribute to the end of the internet bubble. Following this finding, they divide their whole sample into three sub-samples: January 1996-September 1998, October 1998-March 2000 and April 2000-December 2002. They find that the alpha vanishes in the first sub-period and reduces to less than half (of that of the full period) in the last sub-period. They conclude that full period regression creates an *alpha illusion*, "in that any apparent value added by the average fund of funds manager beyond systematic bets took place during the bull market run of October 1998 to March 2000". They also note that "this finding may be uncomfortable for institutional investors in hedge funds because bull market alphas are a redundant feature, at best, of an alternative investment" (Fung and Hsieh (2004), p.73).

These two breakpoints suggested by Fung and Hsieh (2004) are confirmed and employed by other studies that use different sample period and return series.[47] The liter-

[47] See for instance, Fung et al. (2008) and Loviscek and Xu (2010).

Table 3.15: **Risk-adjusted Performance of the Lowest Drawdown Status Portfolios: Controlling for the Backfilling Bias**

This table reports OLS coefficient estimates when excess returns of the lowest drawdown status portfolios are regressed on Fung and Hsieh (2004) seven factors after controlling for the backfilling bias. The sample period is January 1996-December 2009. The first 24 months data of each fund is eliminated in order to control for backfilling bias. See Table 3.2 for the description of portfolio formation. Factors are described in the text. All return series are multiplied by 100 to make the intercepts in percentage form. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Intercept	0.11	0.13	0.12	0.16	0.23**	0.24**	0.23**	0.35**
	(1.03)	(1.26)	(1.21)	(1.57)	(2.07)	(2.29)	(2.25)	(3.62)
SNP	0.19***	0.18***	0.17***	0.22***	0.22***	0.21***	0.20***	0.28***
	(5.87)	(5.85)	(5.99)	(7.48)	(6.89)	(7.22)	(7.38)	(11.46)
SizeSpr	0.14***	0.13***	0.15***	0.16***	0.18***	0.18***	0.18***	0.22***
	(3.16)	(3.05)	(3.72)	(4.28)	(3.89)	(4.12)	(4.14)	(6.61)
FXOpt	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01*
	(1.37)	(1.48)	(1.08)	(1.43)	(1.48)	(1.50)	(1.17)	(1.95)
ComOpt	0.01	0.01	0.01	0.01	0.02**	0.02**	0.02*	0.02**
	(1.61)	(1.41)	(1.15)	(1.50)	(2.29)	(1.97)	(1.89)	(1.98)
BdOpt	-0.01	-0.01	-0.01	-0.01	-0.00	-0.00	-0.00	0.00
	(-1.40)	(-1.33)	(-1.28)	(-1.55)	(-0.48)	(-0.21)	(-0.29)	(0.40)
Bd10Yr	0.09*	0.08*	0.07	0.08*	0.13**	0.12**	0.11**	0.09**
	(1.83)	(1.68)	(1.51)	(1.83)	(2.31)	(2.19)	(2.01)	(2.06)
CredSpr	0.12	0.14	0.12	0.18**	0.13	0.16	0.15	0.18**
	(1.36)	(1.50)	(1.40)	(2.53)	(1.31)	(1.61)	(1.57)	(2.52)
Adjusted R^2	43.8%	43.4%	45.9%	58.2%	47.1%	48.7%	49.0%	67.5%
Number of obs.	168	168	168	168	168	168	168	168

Table 3.16: **Risk-adjusted Performance of the Highest Drawdown Status Portfolios: Controlling for the Backfilling Bias**

This table reports OLS coefficient estimates when excess returns of the highest drawdown status portfolios are regressed on Fung and Hsieh (2004) seven factors after controlling for the backfilling bias. The sample period is January 1996-December 2009. The first 24 months data of each fund is eliminated in order to control for backfilling bias. See Table 3.2 for the description of portfolio formation. Factors are described in the text. All return series are multiplied by 100 to make the intercepts in percentage form. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Intercept	0.55**	0.82***	1.05**	0.16	0.80***	1.20***	1.48***	0.35***
	(2.04)	(2.72)	(2.53)	(1.57)	(3.27)	(4.00)	(3.23)	(3.62)
SNP	0.58***	0.61***	0.50***	0.22***	0.63***	0.61***	0.51***	0.28***
	(7.70)	(8.47)	(4.36)	(7.48)	(10.41)	(8.15)	(4.39)	(11.46)
SizeSpr	0.27***	0.41***	0.40***	0.16***	0.37***	0.54***	0.92***	0.22***
	(3.25)	(4.58)	(2.94)	(4.28)	(4.84)	(5.94)	(4.84)	(6.61)
FXOpt	0.01	0.02	0.03	0.01	0.03	0.02	0.02	0.01*
	(0.67)	(1.28)	(1.40)	(1.43)	(1.59)	(1.35)	(0.72)	(1.95)
ComOpt	-0.00	0.02	0.01	0.01	0.00	-0.01	-0.00	0.02*
	(-0.17)	(0.97)	(0.41)	(1.50)	(0.28)	(-0.33)	(-0.03)	(1.98)
BdOpt	0.01	0.02	0.01	-0.01	0.02	0.03	0.01	0.00
	(0.51)	(0.96)	(0.16)	(-1.55)	(1.49)	(1.47)	(0.27)	(0.40)
Bd10Yr	-0.09	-0.15	-0.17	0.08*	-0.12	-0.20	-0.11	0.09**
	(-0.87)	(-0.96)	(-1.02)	(1.83)	(-1.21)	(-1.61)	(-0.65)	(2.06)
CredSpr	0.13	-0.06	-0.14	0.18**	0.18	0.01	-0.17	0.18**
	(0.72)	(-0.29)	(-0.61)	(2.53)	(0.96)	(0.05)	(-0.77)	(2.52)
Adjusted R^2	45.7%	41.7%	18.0%	58.2%	55.4%	47.8%	27.9%	67.5%
Number of obs.	168	168	168	168	168	168	168	168

ature has also suggested various alternative or complementary breakpoints. Analyzing HFR hedge fund return indices for the period January 1994-December 2002, Kosowski et al. (2007) document a structural break in December 2000, which coincides with the height of the bull market in the late 1990s. Loviscek and Xu (2010), by using a longer sample period of January 1994-December 2008, suggests two complementary breakpoints in median CISDM hedge fund returns: February 2003 and January 2007. February 2003 is associated with a significant upturn in stocks following the significant decline in major equity indices from 2000 through 2002 whereas January 2007 marks the start of the global financial crisis.

All above breakpoints suggested by the literature are identified by using proxies for a typical hedge fund. However, note that the return characteristics of our lowest and highest drawdown status portfolios already point to a divergence from a typical hedge fund. Hence, we further analyze the return series of lowest and highest drawdown portfolios, along with HFR portfolios, for possible breakpoints. June 2008 stands for a clear breakpoint in the HFR and the lowest drawdown status portfolios. September 1998 and March 2000 are confirmed as breakpoints for all HFR and lowest drawdown status portfolios, but not for all highest drawdown status portfolios. For the highest drawdown status portfolio returns, September 1997, February 1999 and August 2008 are identified as breakpoints.[48]

Table 3.17 reports the chi-squared statistics values for Chow tests regarding each breakpoint-return series combination. The lowest drawdown status portfolios show very similar patterns to HFR portfolios. What is striking is that, almost none of the breakpoints suggested in the literature significantly applies to the highest drawdown status portfolios. For these portfolios, significant statistics are obtained using different breakpoints, though never being as strong as the lowest drawdown status portfolios statistics. This implies that there are no extreme changes in the risk structure of the highest

[48] We have analyzed various breakpoints for both lowest and highest drawdown, and HFR portfolios, without constraining ourselves to the exact number of three breakpoints. However, the above mentioned separation of periods gives the maximum adjusted R-squared values overall. Including February 2003 in the lowest drawdown status portfolio breakpoints increases adjusted R-squared values of value weighted portfolio regressions, and decreases those of all others, with all effects being negligible. Hence, we opt to leave February 2003 out in our basic structural break regressions.

Table 3.17: **Structural Breaks Analysis: Chow Test Results**

This table reports the chow test Chi-squared statistics values for the drawdown status portfolio regressions using the breakpoints separately. The breakpoints identified in the literature are: September 1998, March 2000, December 2000, February 2003 and January 2007. Further breakpoints identified from our analysis are: June 2008 for lowest drawdown status portfolios and September 1997, February 1999 and August 2008 for highest drawdown status portfolios. The sample period is January 1996-December 2009. ***, **, and * denote statistical significance of test statistics at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Lowest DS P.								
Sep. 1998	34.61***	26.07***	18.64***	39.02***	16.02**	14.16**	10.99	16.97**
Mar. 2000	26.43***	20.40***	17.85**	23.94***	19.36***	19.89***	19.35***	12.37*
Dec. 2000	36.27***	30.56***	28.36***	26.62***	34.39***	34.21***	33.16***	17.85**
Feb. 2003	25.60***	25.79***	28.10***	20.76***	24.19***	28.67***	32.10***	17.94**
Jan. 2007	47.57***	49.46***	49.97***	35.91***	53.95***	56.92***	59.40***	37.07***
Jun. 2008	50.60***	53.69***	55.25***	43.20***	52.90***	57.88***	57.90***	47.51***
Highest DS P.								
Sep. 1997	4.27	19.42***	24.62***		11.78	18.39**	30.28***	
Sep. 1998	19.36***	12.17*	17.44**		12.18*	10.12	16.55**	
Feb. 1999	26.57***	14.18**	27.22***		18.51***	14.15**	18.06**	
Mar. 2000	10.04	3.18	5.78		2.71	4.43	1.91	
Dec. 2000	11.46	5.87	4.11		2.59	6.62	7.74	
Feb. 2003	12.04*	5.70	5.08		3.60	3.92	8.11	
Jan. 2007	7.38	7.98	7.64		7.59	6.82	13.36*	
Aug. 2008	11.13	6.03	12.08*		14.41**	11.59	18.06**	

drawdown status portfolios, which is further proof for robustness of their outstanding performance.

In Table 3.18, we present the alphas for subperiods obtained from each portfolio's regression after allowing for structural breaks. Let us first analyze the lowest drawdown status portfolios. Note first that using the structural breaks in the regressions improves the adjusted R-squared substantially; there is more than 20% increase in its value for each portfolio. Note also that Chi-squared test statistics are very high, indicating a strong rejection of the null hypothesis that the slope coefficients are the same across the four subperiods.[49] Not surprisingly, the alphas of the lowest drawdown status portfolios are significantly positive only in good market conditions, and significantly negative during the recent financial crisis. The negative coefficients are higher than the positive coefficients in absolute terms, and substantially higher than their full period counterparts. This is exactly the *alpha illusion* mentioned in Fung and Hsieh (2004). Note also that unlike lowest drawdown status portfolios, HFR portfolios do not have significant coefficients in the last period, supporting the insurance seller hypothesis.

On the contrary to lowest drawdown status portfolios, the value and significance level of the alphas of the highest drawdown status portfolios do not change dramatically. Alphas are negative only for the very short period of October 97 to February 99, and these are not significant except one-lag and 3-lag highest drawdown status value-weighted portfolios, perhaps due to some large funds having losses.[50] Alphas are significantly positive for the longest period of March 1999 to August 2008, and more importantly very similar to their full sample values. This also indicates that alphas are not driven by some subperiods, such as the recent financial crisis, where the highest drawdown portfolios perform extremely well.

As a final step, to remove any suspicion on our results, we estimate a regression with four structural breaks for each of our portfolios. We use the breaks suggested in the prior literature, with the exception of replacing January 2007 by June 2008. The Chow test results make it clear that June 2008 is a more appropriate choice for our sample period which is longer than the ones used in the literature.[51] We report the results of this analysis in Table 3.19. As can be seen, all previous results are further confirmed by these regressions. Lowest drawdown status portfolios do not provide significant alphas for the period March 2003 to June 2008, right after the end of the bubble. It is clear that lowest drawdown portfolios perform well only during bull market conditions. On the contrary, highest drawdown status portfolios continue providing positive significant

[49] Similar results are obtained in Fung et al. (2008) for equally weighted portfolio of funds in their sample.

[50] Such a short period in structural break regression is usually ignored in analysis in the literature. See, for instance, Fung and Hsieh (2004).

[51] Using both January 2007 and September 2008 as breaks improves the R-squared negligibly at the expense of having very short periods that are not suitable for analysis. In any case, our results hold with five breakpoints.

alphas for both periods.

3.8 Drawdown Status and Performance: Regression Analysis

In this section we put our theory in the context of the more traditional regression analysis methodology. Our main reference in this section is Agarwal et al. (2009) for two reasons. First, because it provides the most comprehensive setting we are aware of for the testing of hedge funds characteristics. Second, because it analyzes throughfully managerial incentives (total delta), the only hedge fund characteristic that we could not control for in the portfolio sorts methodology.

Following Agarwal et al. (2009), we regress fund returns on a set of controls that include all the hedge characteristics identified as predictive of performance in the existing literature. To be more precise, we estimate the following regressions:

$$\begin{aligned} Return_{i,t} = {} & \alpha_0 + \alpha_1 Total\ Delta_{i,t-1} + \alpha_2 Hurdle\ Rate_i + \alpha_3 High\text{-}water\ Mark_i + \alpha_4 Lockup_i \\ & + \alpha_5 Restriction_i + \alpha_6 Size_{i,t-1} + \alpha_7 Flow_{i,t-1} + \alpha_8 Volatility_{i,t-1} + \alpha_9 Age_{i,t-1} \\ & + \alpha_{10} Management\ Fee_i + \alpha_{11} Return_{i,t-1} + \sum_{s=1}^{3} \alpha_{11+s} I\ Strategy_{i,s} + \xi_{i,t} \end{aligned} \tag{3.3}$$

$$\begin{aligned} Return_{i,t} = {} & \alpha_0 + \alpha_1 Option\ Delta_{i,t-1} + \alpha_2 Managerial\ Ownership_{i,t-1} + \alpha_3 Hurdle\ Rate_i \\ & + \alpha_4 high\text{-}water\ Mark_i + \alpha_5 Lockup_i + \alpha_6 Restriction_i + \alpha_7 Size_{i,t-1} + \alpha_8 Flow_{i,t-1} \\ & + \alpha_9 Volatility_{i,t-1} + \alpha_{10} Age_{i,t-1} + \alpha_{11} Management\ Fee_i + \alpha_{12} Return_{i,t-1} \\ & + \sum_{s=1}^{3} \alpha_{12+s} I\ Strategy_{i,s} + \xi_{i,t} \end{aligned} \tag{3.4}$$

where $Return_{i,t}$ is the net annual return of fund i in year t; $Total\ Delta_{i,t-1}$ is the total expected dollar change in the manager's compensation for a 1% change in the fund i's

Table 3.18: **Structural Breaks Analysis: Regression Results**

This table reports OLS intercepts in percentage form when excess returns of drawdown based portfolios are regressed on Fung and Hsieh (2004) seven factors allowing for structural breaks, where breakpoints are identified separately and specifically for highest and lowest drawdown based portfolios. The breakpoints for lowest drawdown status portfolios are: September 1998, March 2000 and June 2008. The breakpoints for highest drawdown status portfolios are: September 1997, February 1999 and August 2008 for highest drawdown status portfolios. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Lowest DS P.								
Jan. 96 - Sep. 98	-0.14	-0.07	0.05	-0.18	0.07	0.15	0.24**	0.01
	(-0.82)	(-0.43)	(0.34)	(-1.01)	(0.48)	(1.13)	(2.09)	(0.07)
Oct. 98 - Mar. 00	0.80***	0.78***	0.78***	0.68***	0.99***	0.81***	0.81***	0.94***
	(4.16)	(4.37)	(4.51)	(4.04)	(5.05)	(3.89)	(4.30)	(4.32)
Apr. 00 - Jun. 08	0.22**	0.24***	0.23***	0.23***	0.25**	0.28***	0.27***	0.28***
	(2.35)	(2.69)	(2.61)	(2.76)	(2.38)	(2.78)	(2.74)	(3.12)
Jun. 08 - Dec. 09	-0.87**	-0.91***	-0.86**	-0.16	-1.05***	-1.09***	-1.14***	0.07
	(-2.54)	(-2.61)	(-2.33)	(-0.83)	(-2.98)	(-3.40)	(-3.47)	(0.39)
Adjusted R^2	68.4%	69.1%	69.0%	74.2%	71.4%	72.7%	72.7%	79.9%
Chi-sq.(21)	121.40***	118.15***	105.57***	121.46***	92.79***	94.56***	88.35***	88.75***
Highest DS P.								
Jan. 96 - Sep. 97	0.82	1.16	1.26		0.73*	1.11	2.10**	
	(1.15)	(1.29)	(1.53)		(1.65)	(1.64)	(2.05)	
Oct. 97 - Feb. 99	-2.01**	-2.73	-3.32*		-0.46	-0.76	-2.39	
	(-2.21)	(-1.58)	(-1.69)		(-0.74)	(-0.62)	(-1.34)	
Mar. 99 - Aug. 08	0.83***	1.05***	1.26***		0.85***	1.07***	1.03***	
	(3.36)	(4.18)	(3.44)		(3.43)	(3.98)	(3.24)	
Sep. 08 - Dec. 09	3.12***	3.23***	1.64*		3.48***	3.26***	2.73***	
	(6.48)	(3.13)	(1.88)		(6.20)	(4.68)	(3.84)	
Adjusted R^2	63.1%	56.5%	44.9%		68.2%	64.4%	61.3%	
Chi-sq.(21)	60.42***	42.83***	71.30***		49.69***	50.11***	83.31***	

Table 3.19: **Structural Breaks Analysis: Regression Results with Traditional Breakpoints**

This table reports OLS intercepts in percentage form when excess returns of drawdown based portfolios are regressed on Fung and Hsieh (2004) seven factors allowing for structural breaks traditionally employed in the literature. The breakpoints are adopted from the previous literature, with the exception of replacing January 2007 with June 2008. The breakpoints for all portfolios are: September 1998, March 2000, February 2003 and June 2008. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Lowest DS P.								
Jan. 96 - Sep. 98	-0.14	-0.07	0.05	-0.18	0.07	0.15	0.24**	0.01
	(-0.82)	(-0.43)	(0.34)	(-1.01)	(0.48)	(1.13)	(2.09)	(0.07)
Oct. 98 - Mar. 00	0.80***	0.78***	0.78***	0.68***	0.99***	0.81***	0.81***	0.94***
	(4.16)	(4.37)	(4.51)	(4.04)	(5.05)	(3.89)	(4.30)	(4.32)
Apr. 00 - Feb. 03	0.23**	0.27***	0.24**	0.17*	0.37***	0.39***	0.38***	0.28**
	(2.07)	(2.62)	(2.47)	(1.67)	(2.77)	(3.08)	(3.37)	(2.43)
Mar. 03 - Jun. 08	0.20	0.22	0.22*	0.24*	0.21	0.23	0.22	0.28**
	(1.42)	(1.58)	(1.66)	(1.84)	(1.38)	(1.53)	(1.51)	(2.06)
Jul. 08 - Dec. 09	-0.87**	-0.91***	-0.86**	-0.16	-1.05***	-1.09***	-1.14***	0.07
	(-2.54)	(-2.61)	(-2.33)	(-0.83)	(-2.98)	(-3.40)	(-3.47)	(0.39)
Adjusted R^2	67.9%	68.8%	68.9%	73.3%	71.8%	73.6%	73.7%	79.3%
Chi-sq.(28)	124.62***	123.53***	112.96***	120.86***	103.94***	109.69***	104.84***	90.28***
Highest DS P.								
Jan. 96 - Sep. 98	-0.49	-0.42	-0.90		-0.48	-0.40	-0.52	
	(-0.84)	(-0.51)	(-0.86)		(-1.18)	(-0.64)	(-0.52)	
Oct. 98 - Mar. 00	1.10	2.11**	4.84***		1.55	3.01***	2.49**	
	(1.03)	(2.44)	(3.96)		(1.23)	(2.88)	(2.50)	
Apr. 00 - Feb. 03	0.52	1.24**	1.51***		0.38	0.96**	1.37***	
	(1.13)	(2.54)	(2.90)		(0.89)	(2.14)	(2.71)	
Mar. 03 - Jun. 08	0.64**	0.64**	0.58**		0.50***	0.60***	0.48**	
	(2.57)	(2.37)	(2.01)		(2.91)	(2.84)	(1.96)	
Jul. 08 - Dec. 09	3.08***	2.99***	1.50		3.42***	3.19***	2.73***	
	(5.63)	(3.15)	(1.46)		(5.86)	(4.50)	(3.20)	
Adjusted R^2	55.7%	48.1%	37.2%		66.6%	59.8%	57.0%	
Chi-sq.(28)	52.36***	32.04	43.79**		55.89***	44.84*	68.04***	

NAV at the end of year t-1; *Option Delta*$_{i,t-1}$ is the manager's delta from investors' assets in fund i at the end of year t-1; *Managerial Ownership*$_{i,t-1}$ is the ratio of the manager's investment in the fund to the AUM of the fund i at the end of year t-1; *Hurdle Rate*$_i$ is an indicator variable that takes value one if fund i has a hurdle rate, and zero otherwise; *High-water Mark*$_i$ is an indicator variable that takes value one if fund i has high-water mark, and zero otherwise; *Lockup*$_i$ and *Restriction*$_i$ are, respectively, the length of the lockup and restriction periods applied by fund i; *Size*$_{i,t-1}$ is the natural logarithm of the AUM of fund i at the end of year t-1; *Flow*$_{i,t-1}$ is the total dollar flows into (or out of, if negative) fund i during year t-1, scaled by AUM of fund i at the end of year t-1; *Volatility*$_{i,t-1}$ is the annualized standard deviation of the monthly returns of fund i during year t-1; *Age*$_{i,t-1}$ is the age of fund i at the end of year t-1; *Management Fee*$_i$ is the management fee charged by fund i; *Return*$_{i,t-1}$ is the net annual return of fund i in year t-1; each *I Strategy*$_{i,s}$ is a dummy variable that takes value one if fund i belongs to strategy s, and zero otherwise; and $\xi_{i,t}$ is the error term.[52]

As in Agarwal et al. (2009), the analysis in the present section is performed on an annual basis. In order to avoid suspicions on our analysis being biased because of the use of a different data set and sample period to the ones in Agarwal et al. (2009), we first corroborate that their main results hold in our sample. In Table 3.20 we first restate Agarwal et al. (2009) estimation results (for the period 1994-2002). Columns (A) and (B) report their results using the Fama and Macbeth (1973) regression methodology (FMB) for equations (3.3) and (3.4), respectively. Column (C) collects their results after excluding the first two years of data of each fund from the analysis to control for the well-known backfilling bias.[53] In columns (D) to (F) we replicate the previous exercises using the HFR data set for the period 1996-2009.[54] Note that in Column (F) the significance level of managerial ownership decreases substantially and option delta

[52]We have constructed all the variables using the method of Agarwal et al. (2009). For a detailed explanation on the construction of option delta and managerial ownership, see Appendix A in their paper. All variables are winsorized at the 1% level in order to limit the effect of outliers.

[53]See Table VII, row 12, in Agarwal et al. (2009). Backfilling bias occurs because when a fund enters the database, the database providers typically request the full performance history for that fund. Since the choice of entering database typically follows a period of good track-record, this back-filled return history tends to be upward biased. See Ackermann et al. (1999) for a detailed explanation.

[54]In order for the results to be comparable to portfolio analysis and among each other, for all regressions we fix the period at 1996-2009.

even looses significance at conventional levels. Our replication supports the findings of Agarwal et al. (2009) in that: 1) both option delta and managerial ownership have a significant positive effect on performance; and, 2) the importance of these variables on performance deteriorates, both in terms of the size of the coefficient and its significance level, when we eliminate the first two years of data of each fund. This last observation is critical for the purposes of the present paper. The result corroborates that as hedge funds get older, variables that proxy managerial incentives loose their importance. Columns (G) and (H) in table 3.20 further corroborate this conjecture. Here, equations (3.3) and (3.4) are replicated using HFR filtered data set (the first three years of data of each fund are excluded from the analysis in order to define 3-lag drawdown variables). Notice that total delta looses its significance at conventional levels. Hence, it cannot be that incentives are behind our results, as these do not play a very significant role in the context of our filtered data set.

Now we analyze if drawdown status is a hedge fund characteristic related to performance. We focus on equation (3.4) as this is the base model in Agarwal et al. (2009).[55] First of all, we re-estimate the equation after introducing $Drawdown_{i,t-1}$, which is one minus the ratio of the fund's NAV at the end of year t-1 to the maximum NAV reached over the fund's entire history, into the analysis:

$$\begin{aligned} Return_{i,t} = \alpha_0 &+ \alpha_1 Drawdown_{i,t-1} + \alpha_2 Option\ Delta_{i,t-1} + \alpha_3 Managerial\ Ownership_{i,t-1} \\ &+ \alpha_4 Hurdle\ Rate_i + \alpha_5 High\text{-}water\ Mark_i + \alpha_6 Lockup_i + \alpha_7 Restriction_i \\ &+ \alpha_8 Size_{i,t-1} + \alpha_9 Flow_{i,t-1} + \alpha_{10} Volatility_{i,t-1} + \alpha_{11} Age_{i,t-1} \\ &+ \alpha_{12} Management\ Fee_i + \alpha_{13} Return_{i,t-1} + \sum_{s=1}^{3} \alpha_{13+s} I\ Strategy_{i,s} + \xi_{i,t} \end{aligned} \quad (3.5)$$

[55]Our equation (3.4) is referred as the base model (Model 2) in Agarwal et al. (2009) as it includes all available proxies for managerial incentives: manager's option delta, managerial ownership, hurdle rate, and high-water mark.

Table 3.20: **Regression Analysis: First Results**

This table reports Fama and MacBeth (1973) coefficient estimates when *Returns* are regressed on a set of controls using various data sets. Column (A) restates results of Fama and MacBeth (1973) regressions obtained by Agarwal et al. (2009) using the model:

$$\begin{aligned}
Return_{i,t} = \alpha_0 + \alpha_1 \textit{Total Delta}_{i,t-1} + \alpha_2 \textit{Hurdle Rate}_i + \alpha_3 \textit{High-water Mark}_i + \alpha_4 Lockup_i \\
+\alpha_5 Restriction_i + \alpha_6 Size_{i,t-1} + \alpha_7 Flow_{i,t-1} + \alpha_8 Volatility_{i,t-1} + \alpha_9 Age_{i,t-1} \\
+\alpha_{10} \textit{Management Fee}_i + \alpha_{11} Return_{i,t-1} + \sum_{s=1}^{3} \alpha_{11+s} I\ Strategy_{i,s} + \xi_{i,t}.
\end{aligned}$$

In Column (B), Agarwal et al. (2009) results are restated when *Total Delta* is replaced by *Option Delta* and *Managerial Ownership*:

$$\begin{aligned}
Return_{i,t} = \alpha_0 + \alpha_1 \textit{Option Delta}_{i,t-1} + \alpha_2 \textit{Managerial Ownership}_{i,t-1} + \alpha_3 \textit{Hurdle Rate}_i \\
+\alpha_4 \textit{High-water Mark}_i + \alpha_5 Lockup_i + \alpha_6 Restriction_i + \alpha_7 Size_{i,t-1} + \alpha_8 Flow_{i,t-1} \\
+\alpha_9 Volatility_{i,t-1} + \alpha_{10} Age_{i,t-1} + \alpha_{11} \textit{Management Fee}_i + \alpha_{12} Return_{i,t-1} \\
+ \sum_{s=1}^{3} \alpha_{12+s} I\ Strategy_{i,s} + \xi_{i,t}.
\end{aligned}$$

To control for backfilling bias, Agarwal et al. (2009) excludes first two years' data of each fund from the regression and their results are restated in Column (C).

Columns (D) and (E) report the results of these regressions obtained using HFR data set, where sample period is 1996-2009. In Column (F), as in Agarwal et al. (2009), first two years' data of each fund is excluded from the regression. Finally, Columns (G) and (H) report the results of the regressions using HFR filtered data set (which consists of funds with 3-lag drawdown defined). To save from space, coefficients on lag *Size*, *Flow*, *Volatility*, *Age*, *Return* and *Management Fee* are not reported. *Size* is the natural logarithm of the AUM of the fund at the end of the year. *Hurdle rate* is an indicator variable that takes value one if the fund has a hurdle rate, and zero otherwise. *High-water mark* is an indicator variable that takes value one if the fund has high-water mark, and zero otherwise. See Table 3.1 for the definition of variables. All variables are winsorized at the 1% level. Standard errors are Newey-West heteroscedasticity and autocorrelation consistent. The p-values are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Agarwal et al. (2009)			HFR Data Sets				
	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)
Intercept	0.117***	0.113***	Yes	0.071***	0.071***	0.065***	0.052**	0.053**
	(0.000)	(0.000)		(0.001)	(0.001)	(0.001)	(0.026)	(0.019)
Total $\text{Delta}_{i,t-1}$	0.011***			0.006***			0.003	
	(0.003)			(0.000)			(0.420)	
Option $\text{Delta}_{i,t-1}$		0.015**	0.009*		0.007*	0.004		0.005
		(0.017)	(0.083)		(0.094)	(0.420)		(0.412)
Man. $\text{Own.}_{i,t-1}$		0.126***	0.117**		0.040***	0.043**		0.036**
		(0.009)	(0.013)		(0.009)	(0.019)		(0.032)
Hurdle Rate	0.004	0.008	0.006	-0.008	-0.007	-0.006	-0.008	-0.007
	(0.362)	(0.156)	(0.257)	(0.541)	(0.576)	(0.576)	(0.534)	(0.580)
High-water Mark	0.026***	0.026***	0.023***	0.009	0.007	0.008	0.014***	0.012**
	(0.002)	(0.002)	(0.006)	(0.174)	(0.230)	(0.167)	(0.007)	(0.011)
Lockup	0.029*	0.029*	0.028	0.006	0.006	0.011	0.005	0.005
	(0.096)	(0.095)	(0.112)	(0.286)	(0.256)	(0.204)	(0.406)	(0.369)
Restriction	0.018	0.019	0.018	0.012	0.012	-0.006	0.010	0.010
	(0.157)	(0.147)	(0.140)	(0.408)	(0.403)	(0.591)	(0.499)	(0.507)
Adjusted R^2	13.6%	13.8%	13.0%	2.5%	2.6%	1.8%	1.2%	1.4%
Number of obs.	16,901	16,901	14.221	21,739	21,739	16,923	13,556	13,556

We report the results of the FMB regression in Table 3.21 Column (A). Note that drawdown variable is not only highly significant and positively related to performance, but also decreases the effect and significance of option delta and managerial ownership.

Next, we want to analyze how funds in our portfolios perform in regression analysis. For this, we define two indicator variables: *Low* $\textit{Drawdown}_{i,t-1}$ that takes value one if fund i has been in the lowest decile in the last three years (from t-1 to t-3), and zero otherwise; and *High* $\textit{Drawdown}_{i,t-1}$ that takes value one if fund i has been in the highest decile in the last three years, and zero otherwise. Then we estimate equation (3.4), but this time including the *Low Drawdown* and *High Drawdown* variables. More specifically, we estimate the following regression:

$$
\begin{aligned}
Return_{i,t} = \alpha_0 + \alpha_1 Low\ Drawdown_{i,t-1} + \alpha_2 High\ Drawdown_{i,t-1} + \alpha_3 Option\ Delta_{i,t-1} \\
+\alpha_4 Managerial\ Ownership_{i,t-1} + \alpha_5 Hurdle\ Rate_i + \alpha_6 high\text{-}water\ Mark_i \\
+\alpha_7 Lockup_i + \alpha_8 Restriction_i + \alpha_9 Size_{i,t-1} + \alpha_{10} Flow_{i,t-1} \\
+\alpha_{11} Volatility_{i,t-1} + \alpha_{12} Age_{i,t-1} + \alpha_{13} Management\ Fee_i \\
+\alpha_{14} Return_{i,t-1} + \sum_{s=1}^{3} \alpha_{14+s} I\ Strategy_{i,s} + \sum_{s=1}^{13} \alpha_{17+s} I\ Year_{i,s} + \xi_{i,t}
\end{aligned}
\tag{3.6}
$$

In Table 3.21 Column (B), we report the results of this FMB estimation.[56] The variable *High Drawdown* has a significant positive effect on performance whereas *Low Drawdown* does not have a significant effect. In the remaining columns, we report the results of the ordinary least squares (OLS) estimation of these equations under different alternative specifications.[57] In Column (C) we report results from OLS estimation of equation (3.5). Notice that here drawdown has a much stronger effect. Further, the effect of proxies of managerial incentives decrease significantly. In particular, option delta has a significant negative coefficient. This result seriously questions the relationship between incentives and performance. Indeed, according to the incentives theory it should be positive and significant. The negative sign is indeed consistent with our drawdown based theory of performance. Funds with large (small) option delta are funds that tend to be close to (far from) their high-water mark. That is, they tend to be funds in the low (high) drawdown decile. Many of them are just insurance sellers (surviving talented managers). Our analysis suggests that these should exhibit poor (outstanding) performance. Hence, the negative sign of option delta is consistent with our theory and inconsistent with the incentives theory.

In Column (D) we include the two new variables simultaneously in OLS regression, while in Columns (E) and (F) we include them separately. As we can observe, the *High Drawdown* variable always has a highly significant positive coefficient.

[56] Since the number of funds in high drawdown decile portfolios are very few for first three years, we exclude these years from FMB regression and use a sample period of 1999-2009 to get meaningful results.

[57] We focus on pooled OLS regressions because the Fama and MacBeth (1973) regressions deliver very low R^2. In return, year dummies are included in OLS regressions. As in Agarwal et al. (2009), the OLS methodology delivers the strongest results.

Table 3.21: **Regression Analysis: Drawdown Variables**

This table reports OLS coefficient estimates when *Returns* are regressed on various sets of controls using HFR filtered data set. Columns (A) and (C) use the model:

$$\begin{aligned} Return_{i,t} = \alpha_0 + \alpha_1 Drawdown_{i,t-1} + \alpha_2 Option\ Delta_{i,t-1} + \alpha_3 Managerial\ Ownership_{i,t-1} \\ +\alpha_4 Hurdle\ Rate_i + \alpha_5 High\text{-}water\ Mark_i + \alpha_6 Lockup_i + \alpha_7 Restriction_i \\ +\alpha_8 Size_{i,t-1} + \alpha_9 Flow_{i,t-1} + \alpha_{10} Volatility_{i,t-1} + \alpha_{11} Age_{i,t-1} \\ +\alpha_{12} Management\ Fee_i + \alpha_{13} Return_{i,t-1} + \sum_{s=1}^{3} \alpha_{13+s} I\ Strategy_{i,s} + \xi_{i,t}. \end{aligned}$$

Columns (B) and (D) use the model:

$$\begin{aligned} Return_{i,t} = \alpha_0 + \alpha_1 Low\ Drawdown_{i,t-1} + \alpha_2 High\ Drawdown_{i,t-1} + \alpha_3 Option\ Delta_{i,t-1} \\ +\alpha_4 Managerial\ Ownership_{i,t-1} + \alpha_5 Hurdle\ Rate_i + \alpha_6 high\text{-}water\ Mark_i \\ +\alpha_7 Lockup_i + \alpha_8 Restriction_i + \alpha_9 Size_{i,t-1} + \alpha_{10} Flow_{i,t-1} \\ +\alpha_{11} Volatility_{i,t-1} + \alpha_{12} Age_{i,t-1} + \alpha_{13} Management\ Fee_i \\ +\alpha_{14} Return_{i,t-1} + \sum_{s=1}^{3} \alpha_{14+s} I\ Strategy_{i,s} + \sum_{s=1}^{13} \alpha_{17+s} I\ Year_{i,s} + \xi_{i,t}. \end{aligned}$$

The type of regressions are also different. Columns (A) and (B) report Fama and and MacBeth (1973) coefficient estimates with Newey-West heteroscedasticity and autocorrelation consistent standard errors. Columns (C), (D), (E) and (F) report OLS regression results after correcting standard errors for within-cluster correlation, heteroskedasticity and autocorrelation. The sample period is 1996-2009, except in Column (B) where it is set as 1999-2009 for meaningful regression results. *Low Drawdown* is an indicator variable that takes value one if the fund has been in the lowest decile in the last three years, and zero otherwise. Similarly, *High Drawdown* is an indicator variable that takes value one if the fund has been in the highest decile in the last three years, and zero otherwise. To save from space, coefficients on lag *Size*, *Flow*, *Volatility*, *Age*, *Return* and *Management Fee* are not reported. See Tables 3.1 and 3.20 for the definition of variables. All variables are winsorized at the 1% level. The p-values are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	FMB		OLS			
	(A)	(B)	(C)	(D)	(E)	(F)
Intercept	0.047**	0.045*	0.134***	0.146***	0.150***	0.146***
	(0.030)	(0.073)	(0.000)	(0.000)	(0.000)	(0.000)
$\text{Drawdown}_{i,t-1}$	0.181**		0.369***			
	(0.014)		(0.000)			
Low $\text{Drawdown}_{i,t-1}$		-0.006		-0.004	-0.006	
		(0.360)		(0.410)	(0.181)	
High $\text{Drawdown}_{i,t-1}$		0.070*		0.049***		0.050***
		(0.079)		(0.008)		(0.007)
Option $\text{Delta}_{i,t-1}$	0.004	0.006	-0.013**	-0.011**	-0.010*	-0.012**
	(0.456)	(0.513)	(0.019)	(0.039)	(0.063)	(0.033)
Man. $\text{Ownership}_{i,t-1}$	0.035**	0.041**	0.045***	0.045***	0.043***	0.045***
	(0.036)	(0.048)	(0.000)	(0.000)	(0.001)	(0.000)
Hurdle Rate	-0.011	0.002	0.006	0.010	0.010	0.010
	(0.391)	(0.862)	(0.253)	(0.110)	(0.111)	(0.115)
High-water Mark	0.013***	0.011**	0.008	0.010	0.007	0.007
	(0.008)	(0.033)	(0.202)	(0.120)	(0.280)	(0.257)
Lockup	0.005	0.002	0.005	0.005	0.006	0.006
	(0.407)	(0.715)	(0.181)	(0.203)	(0.163)	(0.163)
Restriction	0.011	0.002	0.010	0.007	0.014*	0.014*
	(0.441)	(0.879)	(0.194)	(0.265)	(0.082)	(0.088)
Adjusted R^2	2.9%	2.5%	25.0%	23.6%	23.5%	23.6%
Number of obs.	13,556	12,673	13,556	13,556	13,556	13,556

In summary, the results derived in this section clearly establish that drawdown status is a genuine hedge fund characteristic related to performance. These results together with those derived in the portfolio sorts methodology further corroborate that drawdown status is also a very relevant characteristic in quantitative terms. Finally, we reiterate that our analysis severely questions the role played by incentives in hedge funds' performance.

3.9 Concluding Remarks

This paper introduces drawdown status analysis as a new way of thinking about hedge fund performance. The analysis combines hedge fund management meritocracy with investors revealed preferences and establishes drawdown status as a key hedge fund characteristic related to performance.

The analysis delivers four, we believe, completely new insights on hedge funds. First, the presence of insurance selling in the industry is large enough to make portfolios of low drawdown funds weak performers in general and bad performers in times of turmoil. Second, the market operates a Darwinian selection process according to which funds running large drawdowns for a prolonged period of time are managed by truly talented traders who deliver outstanding future performance. Third, a completely new dimension of risk arises as a distinctive feature of hedge funds: risk conditional on survival is tantamount to outstanding performance. Fourth, drawdown status analysis raises serious concerns about the role played by other hedge fund characteristics –such as total delta– on fund performance and casts doubt on the validity of some performance evaluation measures –such as the Calmar and Sterling ratios– that are widely used in practice.

As a premier on drawdown status analysis, this paper leaves many issues unaddressed. First, our analysis focuses only on the analysis of the two extreme drawdown deciles; naturally, a more comprehensive analysis is a fruitful topic for future research. In particular, the analysis of the portfolio of funds that survive after hitting the largest drawdown decile, irrespectively of whether they stay in the largest drawdown decile (analyzed here) or move to lower deciles (not analyzed here) deserves special attention as it fits closer the Darwinian dichotomy between death and survival. Second, we believe that much could be learned by comparing the role played by drawdown status in hedge funds versus mutual funds. Some of our results here depend critically on the high-water mark clause, which is ubiquitous in the hedge fund industry but nearly absent in the world of mutual funds; hence, mutual funds are a good control group for testing our hypothesis. This also seems to be a good venue for future research. Third, the present analysis is short to fully account for the seemingly paradoxical situation of an investment community sophisticated enough to sort talented managers among those suffering large drawdowns, but naive when investing in low drawdown funds. Finally, we open but do not address the debate on the Darwinian mechanism operating in other markets. In particular, we suggest that it can have some bearing on the anomalous pricing of distress stocks. The analysis of these two last issues is also a top priority in our research agenda.

Chapter 4

What Do Outside Directors Learn At Board Meetings?

4.1 Introduction

Over the last decade, outside directors have been at the focus of a debate on their monitoring and advising roles both in the corporate and the academic world. An outside director is a director who has never worked at the company or any of its subsidiaries. On the one hand, outside directors are better positioned for their duties related to monitoring the executives as their incentives are better aligned with those of the shareholders. On the other hand, since they are less informed about the firm's daily activities with respect to their executive counterparts, they have a disadvantage in performing their advising duties. Moreover, the information they obtain on the firm is provided mainly by the CEO and other executives, hence might be biased towards those individuals' interests. The question that follows from this argument is: Do the outside directors know enough about their firms so as to perform their duties satisfactorily? One way to deal with this question is to analyze how well they get informed during the board meetings as these constitute outside directors' primary information source regarding firm's activities. This paper is a first attempt to evaluate the informational content of board meetings for outside directors by analyzing their trades the around meeting dates.

Board meetings are important events for two reasons. First, prior to a board meeting, relevant information will be collected by the executives in preparation for the meeting and communicated to the directors in advance. Second, during the board meeting, there will be discussions among board members and important decisions will be taken (Mishraa, Rowe, Prakash, and Ghosh 2009; Vafeas 1999). If firm's executive officers and directors act on the information gathered before and during the board meetings, one would expect to observe them trading extensively both shortly before and after these events. Directors, officers and large stockholders (beneficial owners of more than 10% of any class of firm equity) are considered as *insiders* and are required to file their trading activity with the U.S. Securities and Exchange Commission (SEC). Using this data, along with the annual board meeting dates of 3,042 distinct firms obtained from Riskmetrics database, I find that the overall level of insider trading hikes on the day of the meeting and the day following it. What is more interesting is the trading behavior of the outside directors as compared to that of the executives. Executives purchase frequently both prior and posterior to the meetings, whereas outside directors significantly increase their trading frequency right after the board meetings. This is consistent with the view that executives trade on the information they collect before (and during) the board meetings whereas outside directors trade on the information acquired during the meetings. Not surprisingly, no significant pattern is observed regarding trades of insiders who do not contribute to the board meetings.

An interesting question arises from the previous analysis. Are board meetings useful in bridging the information gap between the inside and outside members of the board? In a more general context, Ravina and Sapienza (2010) compare the trading performance of independent directors and executives. They find that independent directors earn positive abnormal returns when they purchase their company stock, and that the difference from the same firm's executives is relatively small. They use this evidence to argue that independent directors have enough information to monitor the company executives. However, they relate this phenomenon to the incentives of independent directors for collecting relevant information while serving on the firm's board. On the contrary, I focus directly on the information they gather via the board meetings, which is mostly prepared by the company officers. This subject deserves special attention as it is crucial in understanding whether the outside directors are kept in the dark by their executive counterparts or not.

Analyzing the trading behavior of insiders with respect to the date of the board meetings provides interesting results. First of all, outside directors earn substantial abnormal returns for their purchases around the board meetings at most horizons.[1]

[1]Following Ravina and Sapienza (2010), I consider positions mimicking that of the insiders trades

This effect is robust to the inclusion of firm fixed effects and controlling for transaction size and individual's holdings. This is also consistent with the previous studies that demonstrate the profitability of insiders trades without constraining to specific periods (Finnerty 1976; Jaffe 1974; Jeng, Metrick, and Zeckhauser 2003; Lakonishok and Lee 2001; Lin and Howe 1990; Marin and Olivier 2008; Ravina and Sapienza 2010; Rozeff and Zaman 1988; Seyhun 1986, 1998). Second, outside directors earn higher returns when their trade is initiated after the board meetings as compared to when it is initiated before attending the meetings. This provides evidence on that board meetings constitute an important source of information for outside directors. Moreover, when I compare the trading performance of outside directors vis-à-vis their firm's executives, I find that directors earn significantly higher market adjusted returns in the subsample of purchases initiated after the board meetings. This does not hold for the subsample of purchases prior to the board meetings. This finding suggests that outside directors are adequately informed about the firm by the executives during the board meetings; an observation that underlines meetings' importance for directors' advising and monitoring duties.

I perform a similar analysis for outside directors sales, however I find only modest corresponding evidence regarding these. This is consistent with the literature which documents that unlike purchases, sales can be driven by diversification or liquidity reasons, thus, are not necessarily information driven (Jeng, Metrick, and Zeckhauser 2003; Lakonishok and Lee 2001; Ravina and Sapienza 2010). Moreover, analyzing a period around the board meetings introduces further noise since awards and grants are more likely to be transferred to insiders during the board meetings, which may result in an increased selling pressure around meeting dates.

This paper contributes to the literature on the board of directors by supporting a positive attitude towards outside directors. Weisbach (1988), Byrd and Hickman (1992) and Cotter, Shivdasani, and Zenner (1997) demonstrate evidence on the monitoring role of outside directors. Nevertheless, many early studies regarding the composition of board of directors do not find a significant effect of outside directors on firm's performance (Bhagat and Black 2001; Hermalin and Weisbach 1991; Klein 1998). However, Hermalin and Weisbach (1998) note that endogeneity of board composition may be playing a role in failing to find a relationship.[2] Recent literature provides theoretical background (Adams and Ferreira 2007; Harris and Raviv 2008) and empirical evidence (Boone, Field, Karpoff, and Raheja 2007; Coles, Daniel, and Naveen 2008; Duchin, Mat-

and holding it for 0, 30, 60, 90 and 180 trading days.

[2]Hermalin and Weisbach (2003) provide an excellent review of the literature on boards of directors.

susaka, and Ozbas 2010; Linck, Netter, and Yang 2008) on that the boards of directors are endogeneously determined according to the firm's monitoring and advising needs. This study contributes to this literature by showing that board meetings of large firms tend to diminish informational disadvantage of outside directors, enhancing their advising capabilities. It would be interesting to further analyze the relationship between the board characteristics of the firms and performance of their directors trades.

This paper further contributes to the literature by identifying information driven insider trading through focusing on the period around the board meetings. There is recent work that tries to uncover the informativeness of insider trades. For example, Scott Jr. and Xu (2004), by using a variable for shares traded as a percentage of insiders' holdings, separates information driven sales from sales driven by liquidity or diversification motives. They find that large insider sales that also accounted for large percentages of insiders' holdings had significant predictive power whereas small sales didn't. Similarly, Jenter (2005) controls for recent changes in manager's equity holdings to sort out diversification or rebalancing driven insider trading. Most recently, Cohen, Malloy, and Pomorski (2012) show that there is predictable, identifiable routine insider trading that is not informative. By filtering out routine trades, they can attribute all available abnormal returns solely to the remaining transactions, those of whom they call opportunistic traders. However, these studies uncover informativeness of insiders trades by using proxies for the motives behind trading that sort out the non-information driven insider trading. On the contrary, this study focuses directly on information driven trades since the exact date of the informational event, the board meeting date, is observable. In that, this paper is more related to Damodaran and Liu (1993) who analyze insider trading around reappraisals of real estate investment trusts and demonstrate the information contained in these events.

Finally, this paper sheds new light on the significance of board meetings. Vafeas (1999) provides the first study to point out the role of the board meetings by analyzing the relation between board meeting frequency and firm performance. He finds that the annual number of board meetings is inversely related to the firm value, but the effect is driven by increased frequency of board meetings following share price declines. He suggests that board activity is an important element in board's efficacy through enhancing monitoring and advising contributions from firm's directors. Mishraa, Rowe, Prakash, and Ghosh (2009) analyze the spread behavior around board meetings for firms with concentrated insider ownership. They find that for such firms, the bidask spread significantly changes around the meeting date and they relate this to the increased insider trading activity during the same period. They make the point that board meetings are important informational events. However, their work is constrained to a sample of firms that have concentrated ownership (a sample of only 40 firms) and they do not distinguish among the insider groups.

The paper is organized as follows. Section 4.2 explains the data and offers descriptive statistics. Distribution of insider trading around board meetings is reported in Section 4.3. Section 4.4 analyzes the trading performance of insiders transactions. Section 4.5 concludes.

4.2 Data and Descriptive Statistics

Corporate insiders are defined broadly to include all individuals "that have access to non-public material, insider information", and these individuals are required to report their trading activity with the SEC. TFN Insider Filing database covers all insider trading information reported on SEC Forms 3, 4 and 5. Form 4 is the most important insider document as it reports any change in an insider's ownership position. It could be a purchase, sale, option grant, option exercise , gift, etc. Form 3 is the initial statement of beneficial ownership for all officers. Form 5 is the annual statement of change in beneficial ownership which contains activity for exempt transactions not required on a Form 4. TFN Insider Filing database provides the name of the insider, the position she holds with respect to the firm (CEO, chairman of the board, director, large shareholder, etc.), transaction date and price, shares bought/sold, and shares held by the insider as a result of the transaction. Following the literature (Lakonishok and Lee 2001; Ravina and Sapienza 2010), I only analyze open market purchases and sales of insiders with a minimum of 100 shares traded to focus on meaningful events.[3]

The insiders include company executives, directors, large shareholders (who own at least 10% of the company shares), affiliates, controllers, etc. The focus of this study is on *outside directors*, who are defined as nonexecutive directors. However, following Ravina and Sapienza (2010), I also divide this group into two: *independent directors* who are outside directors that are not large shareholders, and *outside blockholders* who are out-

[3]As advised in Thomson Reuters Insider Trading overview, observations with cleanse code S or A are excluded from the analysis. The data with a cleanse code of S have a different security from the one they have been entered under. Cleanse code A flags cases where several of the data elements are invalid or missing.

side directors that also own a minimum of 10% share in the company. Due to their large ownership, outside blockholders may have different incentives and better information regarding the firm than the independent directors, hence it would be interesting to analyze their trades separately. *Executives* are the biggest group of insiders, and note that they include directors who also hold executive positions in the firm. All the remaining insiders will be classified as *other insiders* throughout the study.

My source of board of directors data is Riskmetrics Directors database. This database covers mainly S&P 1500 companies from the year 1996 onwards and provides data on the identity and characteristics of board directors. Riskmetrics obtains information from annual board meetings of companies, and the relevant date of the board meeting is provided in the data set. The directors data consists of 3,374 distinct firms, 34,044 distinct individuals, and spans the period from 1996 to 2010. I merge the insider trading data with this database. A total of 3,265 firms, which is 96.8% of the whole sample, have some of their insiders trading in the period 1996-2010 with the data being available in the TFN Insider Filing database.

To capture the trading that is driven by information released around the board meetings, I focus on open market purchases and sales transactions that take place within one month window of the board meeting date. To be more precise, I consider all trades executed between 15 days before and 14 after the board meeting date [D-15,D+14], where D denotes the day of the annual board meeting. The choice of the window follows from Mishraa, Rowe, Prakash, and Ghosh (2009) who analyze the bidask spread around meeting dates in the same manner. It is important to include days prior to the meeting dates, because the directors typically receive company financial reports prior to the board meetings. Even though the period of communicating company information to the directors will show variety for companies, 15 days window will most probably capture all the information released to directors prior to the meetings. The analysis in this paper will draw its conclusions by analyzing the change in trading behavior and performance of outside directors after the board meeting dates [D,D+14] to sort out the value of the information acquired by the outside directors during board meetings.

The final sample consists of 145,298 transactions in the period 1996-2010, which covers insider trading within one month window of a total of 17,163 board meetings of 3,042 distinct firms. Table 4.1 reports the distribution of the annual board meetings with respect to meeting months and years. It is important to note that with regard to Riskmetrics data set, annual meetings almost always take place in the same month of

Table 4.1: **Distribution of the Annual Board Meetings**

This table presents the distribution of the annual board meetings with respect to meeting month and year. The sample consists of 17,163 annual meetings of 3,042 distinct firms in the period 1996-2010.

	Meeting Month												
Year	January	February	March	April	May	June	July	August	September	October	November	December	Total
1996	32	30	36	326	361	69	25	18	31	46	38	14	1,026
1997	39	43	34	313	440	66	36	33	26	51	48	11	1,140
1998	51	49	41	347	509	95	37	31	28	46	53	11	1,298
1999	45	55	42	313	517	90	38	28	40	42	48	21	1,279
2000	41	52	35	283	493	115	34	28	35	44	50	19	1,229
2001	43	44	37	258	566	122	38	33	31	36	52	23	1,283
2002	38	48	32	259	457	85	29	20	24	29	45	10	1,076
2003	29	31	29	239	434	102	32	23	30	38	48	18	1,053
2004	36	44	48	260	457	94	28	28	30	38	44	19	1,126
2005	34	49	39	247	463	104	26	34	28	31	46	22	1,123
2006	38	40	31	229	498	87	23	31	33	38	39	12	1,099
2007	33	37	36	228	565	101	33	38	19	36	40	17	1,183
2008	36	30	32	232	532	117	30	27	24	34	26	13	1,133
2009	31	30	30	198	442	117	23	33	23	26	32	18	1,003
2010	34	35	37	221	556	133	19	23	11	13	22	8	1,112
Total	560	617	539	3,953	7,290	1,497	451	428	413	548	631	236	17,163

every year for each company.

Restricting attention to insider transactions around board meetings of large public companies covered in Riskmetrics database induces some sample characteristics in the data. To demonstrate its effects clearly, Table 4.2 presents the distribution of the insider purchases and sales along with the insider types for various insider trading samples. I start by analyzing the whole insider trading sample for the period 1996-2010 obtained from TFN Insider Filing database. Panel A reports a total of 659,982 purchases which is almost equally shared across groups of executives, outside directors and other insiders.[4] Sales show a different pattern in the sense that out of 2,344,548 transactions, almost half of them (1,506,708) are executed by the executives.

Panel B of Table 4.2 compares this whole TFN Insider Filing sample with the subsample of transactions that belong to the firms covered in the Riskmetrics database. Note that these are large public firms. This sample contains 224,962 purchases (around one third of the whole sample) with a distribution among the insider types very similar to that of the whole sample. 1,508,315 sale transactions in this sample exhibit a similar pattern, with even a higher ratio of executive sales. Overall, the sample covered in Riskmetrics is a good representation of the whole sample.

Panel C of Table 4.2 reports the characteristics of the final sample, where only the transactions executed within 15 days of the board meetings are considered. Contradicting with previous samples, the biggest portion of 11,971 insider sales pertain to outside directors, followed by executives, and other insiders. Nevertheless, insider sales show a similar pattern to the whole sample since the majority of a total of 134,277 insider sales have been initiated by the executives.

4.3 Distribution of Insider Trading Around Board Meetings

In this section, I analyze the distribution of insider transactions with respect to the annual board meeting dates. Board meetings are important events for not only the decisions taken during them, but also for the substantial information gathering taking place in advance (Mishraa, Rowe, Prakash, and Ghosh 2009; Vafeas 1999). If firm

[4] In panels A and B, to have a meaningful comparison, observations where share price is less than 2 dollars are excluded as in other studies.

Table 4.2: **Insider Trading Samples by Transaction and Insider Types**

This table presents the distribution of the insider trading data. The insiders include company executives, directors, large shareholders (who own at least 10% of the company shares), affiliates, controllers, etc. The first group consists of *executives* who hold executive positions in the firm along with possible directorship positions. The second group denotes the *outside directors* who are nonexecutive directors of the firm. This group consists of two subgroups: *independent directors* who are outside directors that are not large shareholders, and *outside blockholders* who are outside directors that own a minimum of 10% share in the company. All the remaining insiders are classified as *other insiders.* Panel A presents the whole insider trading sample that contains all open market purchases and sales of insiders for the period 1996-2010. Panel B presents the sample obtained by merging the whole sample by Riskmetrics database, which basically consists of S&P 1500 companies. Panel C presents the final sample that contains all insider trades executed between 15 days before and 14 after the annual board meeting dates obtained from Riskmetrics database. The statistics regarding transaction values are calculated over the total transactions by each insider group, whereas those regarding number of transactions are calculated by individual, firm, and year.

	Panel A: TFN Insider Filing Sample					
	Min.	Max.	Mean	Median	Std. Dev.	Total
	Purchases: Transaction in Numbers					
Executives	1	958	2.97	1	8.92	214,198
Independent Directors	1	705	2.68	1	6.31	206,556
Outside Blockholders	1	776	7.67	2	30.42	24,546
Other Insiders	1	5,664	14.82	2	98.06	214,682
	Purchases: Value in Dollars					
Executives	200	2,221,536 mil.	18,434,479	12,000	5,005 mil.	3,936,996 mil.
Independent Directors	200	4,500,000 mil.	22,040,118	13,870	9,916 mil.	4,538,700 mil.
Outside Blockholders	200	41,666 mil.	2,639,277	14,625	269 mil.	64,559 mil.
Other Insiders	200	624,099 mil.	6,928,614	21,093	1,647 mil.	1,483,361 mil.
	Sales: Transaction in Numbers					
Executives	1	11,833	8.97	2	64.09	1,506,708
Independent Directors	1	2,031	7.09	2	34.08	460,894
Outside Blockholders	1	6,064	20.26	2	165.97	82,691
Other Insiders	1	5,677	12.15	2	81.56	294,255
	Sales: Value in Dollars					
Executives	200	414,011 mil.	663,062	35,640	338 mil.	998,728 mil.
Independent Directors	200	7,350 mil.	578,258	35,062	14 mil.	266,386 mil.
Outside Blockholders	200	14,000 mil.	1,936,922	27,479	55 mil.	160,067 mil.
Other Insiders	200	807,142 mil.	5,343,762	41,900	1,489 mil.	1,570,676 mil.

Table continues to next page.

	Panel B: TFN Insider Filing - Riskmetrics Merged Sample					
	Min.	Max.	Mean	Median	Std. Dev.	Total
	Purchases: Transaction in Numbers					
Executives	1	958	2.81	1	11.16	67,222
Independent Directors	1	705	2.57	1	7.30	66,938
Outside Blockholders	1	509	9.39	2	33.67	4,966
Other Insiders	1	5664	25.37	3.00	191.06	85,836
	Purchases: Value in Dollars					
Executives	204	884 mil.	210,025	21,845	5 mil.	14,104 mil.
Independent Directors	200	836 mil.	214,618	23,760	4 mil.	14,360 mil.
Outside Blockholders	217	375 mil.	1,114,587	30,095	11 mil.	5,521 mil.
Other Insiders	200	26,511 mil.	1,823,527	20,730	110 mil.	156,480 mil.
	Sales: Transaction in Numbers					
Executives	1	11,833	9.58	2	75.02	1,023,294
Independent Directors	1	1,612	7.41	2	32.73	271,899
Outside Blockholders	1	6,064	34.31	3	258.14	52,328
Other Insiders	1	5,677	17.59	2	124.72	160,794
	Sales: Value in Dollars					
Executives	203	10,443 mil.	415,393	48,600	16 mil.	425,015 mil.
Independent Directors	202	7,350 mil.	642,813	53,434	16 mil.	174,743 mil.
Outside Blockholders	500	14,000 mil.	2,021,599	41,232	67 mil.	105,780 mil.
Other Insiders	216	6,188 mil.	2,598,982	50,490	42 mil.	417,851

	Panel C: Final Sample - Insider Trading Around Board Meetings					
	Min.	Max.	Mean	Median	Std. Dev.	Total
	Purchases: Transaction in Numbers					
Executives	1	116	2.09	1	5.08	3,845
Independent Directors	1	114	1.76	1	3.46	5,343
Outside Blockholders	1	20	3.81	2.50	4.20	99
Other Insiders	1	1,028	10.44	2	65.80	2,684
	Purchases: Value in Dollars					
Executives	125	10 mil.	161,347	30,856	0.518 mil.	620 mil.
Independent Directors	382	91 mil.	192,106	27,074	1.584 mil.	1,026 mil.
Outside Blockholders	1,540	34 mil.	1,075,551	66,960	4.967 mil.	106 mil.
Other Insiders	594	7,044 mil.	5,850,077	16,345	190 mil.	15,701 mil.
	Sales: Transaction in Numbers					
Executives	1	1,706	5.51	2	24.79	92,888
Independent Directors	1	414	4.85	2	14.96	25,552
Outside Blockholders	1	1,396	22.47	3	116.09	3,573
Other Insiders	1	692	13.59	2	53.14	12,314
	Sales: Value in Dollars					
Executives	198	773 mil.	418,867	54,264	5 mil.	38,907 mil.
Independent Directors	478	378 mil.	606,685	64,218	6 mil.	15,502 mil.
Outside Blockholders	1,146	897 mil.	970,564	63,138	17 mil.	3,466 mil.
Other Insiders	414	1,479 mil.	1,522,729	59,555	21 mil.	18,750 mil.

executives and directors act on the information gathered before and during the board meetings, one would expect to see insider trading both prior and posterior to the board meetings.

Figure 4.1 presents the distribution of open market purchase transactions of the insiders around the board meeting dates. More specifically, the meeting date is considered as point 0 on the x-axis. All transactions to the left of this point has been executed before the meeting took place. These purchases may be driven by the data collected in preparation of the meeting and its communication to directors and other insiders. All purchases on the meeting date and after that are more likely to be driven by the information provided at the board meetings, along with the new decisions taken regarding firm's future actions.

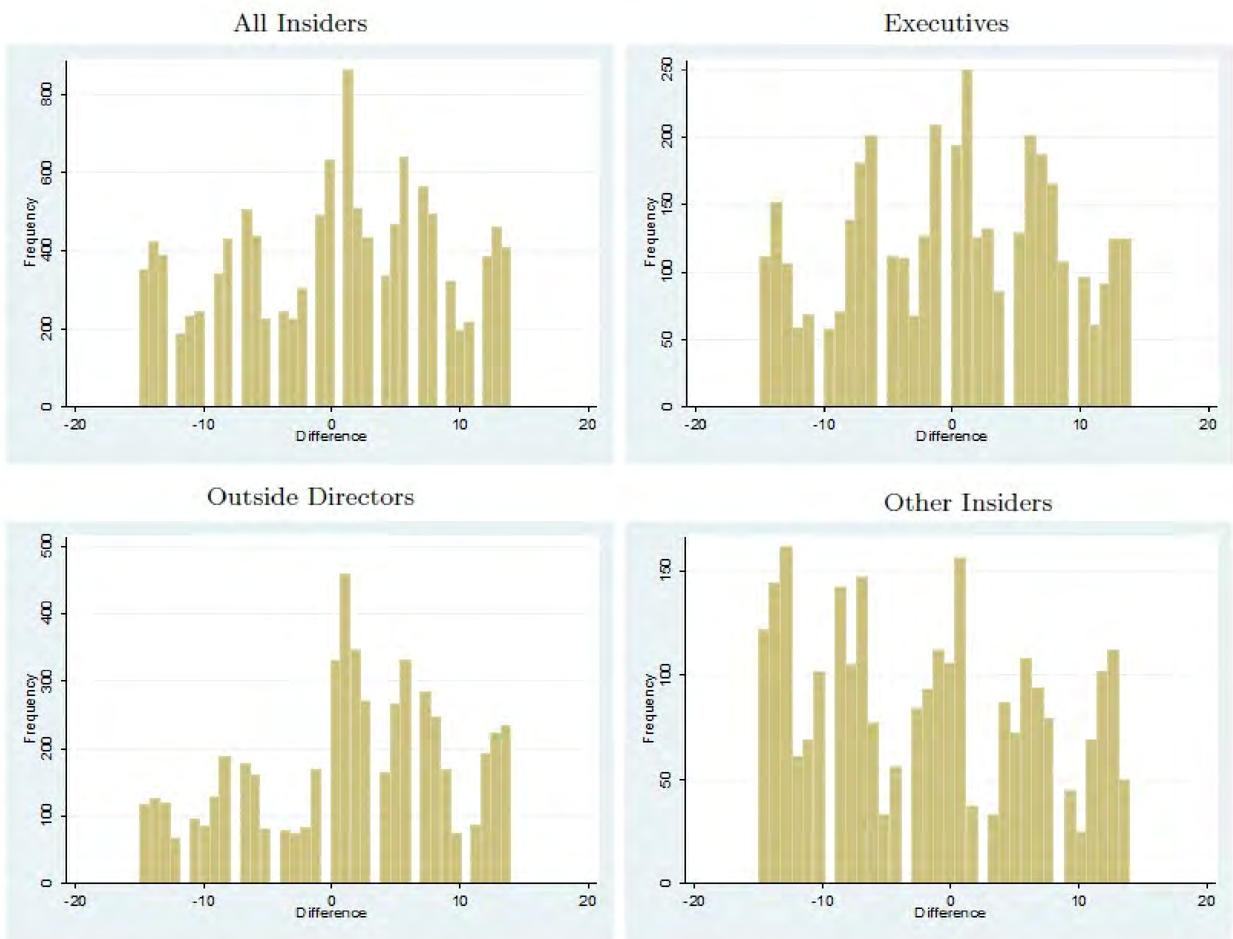

Figure 4.1: **Distribution of Insiders Purchases Around Board Meetings.** This figure presents the distribution of open market purchase transactions of all insiders, executives, outside directors and other insiders, respectively, around the board meeting dates. *All insiders* are classified into three groups: *executives*, *outside directors* who are nonexecutive directors, and *other insiders*. *Difference* refers to days with respect to the date of the annual board meeting obtained from Riskmetrics database, and takes value between -15 to +14. The sample period is 1996-2010.

An interesting picture emerges from analyzing the behavior of various insider groups in Figure 4.1. First of all, notice that the overall level of insider trading hikes at the day of the meeting and the day following it. Executives trade heavily within 10 days window around the board meetings, with no significant difference in their behavior prior vs. posterior to the meeting. However, the outside directors significantly increase their trades right after the board meetings. This is consistent with the idea that executives trade on the information they collect before the board meetings whereas outside directors get informed during the board meetings and use this information in trading. Consistent with the significance of board meetings in information acquisition, there is no increase in the trading of other insiders who do not attend the meetings; if any, there is a slight decrease.

Complementing the previous analysis, Figure 4.2 presents the distribution of open market sale transactions of the insiders around the board meeting dates. Unlike insider purchases, insider sales do not exhibit a clear pattern. Outside directors trade more frequently after the board meetings but the difference with respect to those before the meetings is not substantial. This is consistent with the idea that unlike purchases, sales can be driven by portfolio rebalancing needs, hence are not necessarily information driven. Moreover, analyzing a period around the board meetings introduces further noise since awards and grants tend to be transferred to insiders during the board meetings and as a result selling pressure may increase.

Table 4.3 provides a numerical representation of the distribution of the sale and purchase transactions of insider groups with respect to board meeting dates. Panel A splits the transactions into two categories as before or after the meeting date. Independent directors increase their purchase (sale) transactions by 115% (28%) from 1,696 to 3,647 as compared to the executives who only increase by 17% (20%) from 1,771 to 2,074 after the board meetings. For a better comparison, I compute the differences in mean number of transactions for each group. On average, a firm's independent directors together execute 1.64 purchase transactions after the board meetings. This compares to an average of 0.76 before the meetings. The difference, which is 0.88 transactions, is statistically significant at 1% level. Even though the cumulative sales are not so different among prior vs. posterior periods, a similar difference (0.81 transactions) is reported for the average number of sales with the same significance level. In contrast, we do not observe a significant change in the trades of executives after the board meetings. Average sales are significantly higher but the difference is negligible.

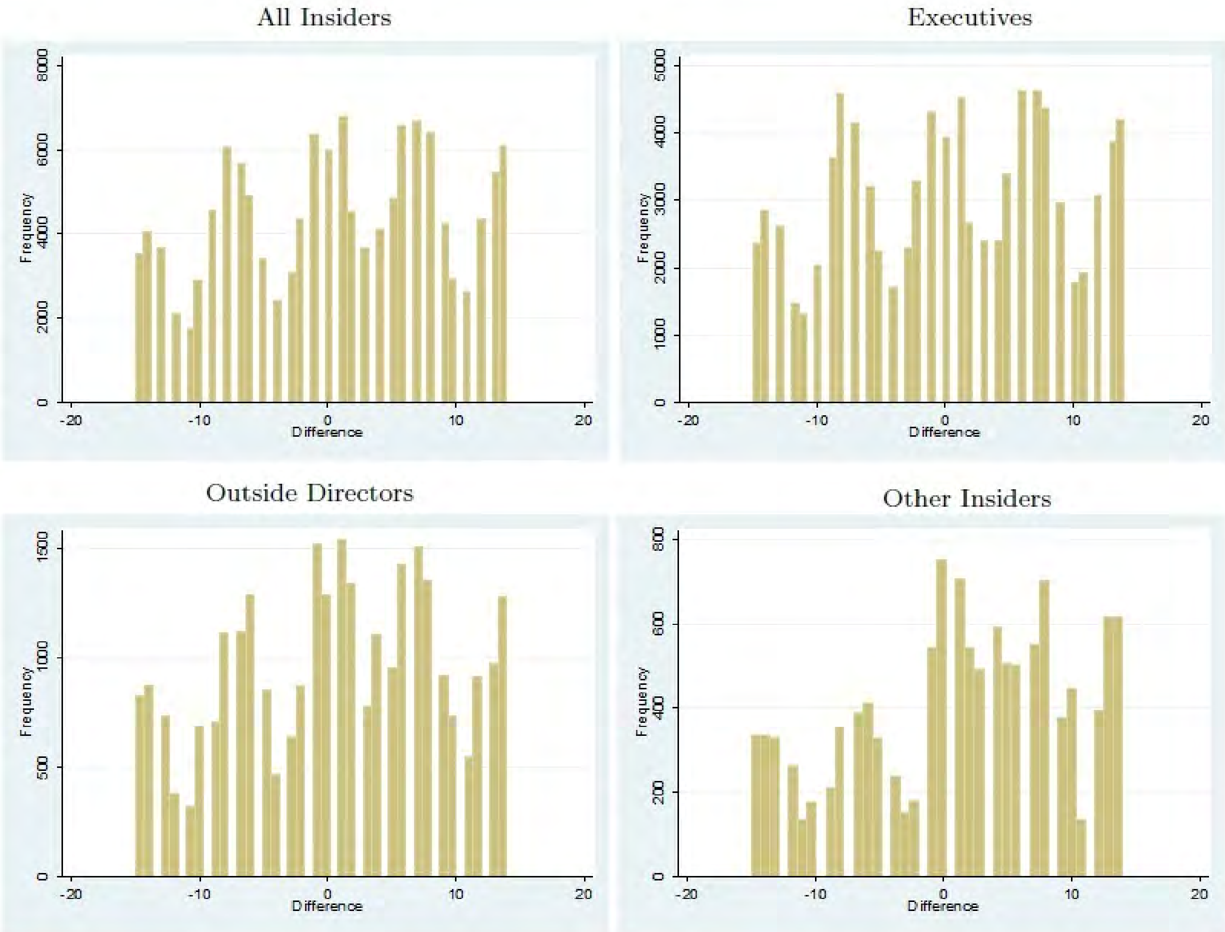

Figure 4.2: **Distribution of Insiders Sales Around Board Meetings.** This figure presents the distribution of open market sale transactions of all insiders, executives, outside directors and other insiders, respectively, around the board meeting dates. *All insiders* are classified into three groups: *executives*, *outside directors* who are nonexecutive directors, and *other insiders*. *Difference* refers to days with respect to the date of the annual board meeting obtained from Riskmetrics database, and takes the value between -15 to +14. The sample period is 1996-2010.

Table 4.3: **Distribution of Insiders Transactions in the Board Meetings Sample**

This table presents the distribution of the insider trading data in the final sample that contains all trades executed between 15 days before and 14 after the annual board meeting dates obtained from Riskmetrics database. The insiders include company executives, directors, large shareholders (who own at least 10% of the company shares), affiliates, controllers, etc. The first group consists of *executives* who hold executive positions in the firm along with possible directorship positions. The second group denotes the *outside directors* who are nonexecutive directors of the firm. This group consists of two subgroups: *independent directors* who are outside directors that are not large shareholders, and *outside blockholders* who are outside directors that own a minimum of 10% share in the company. All the remaining insiders are classified as *other insiders*. Panel A splits the transactions into two categories as before and after the meeting date (D) and reports the total number of transactions for each insider group along with the percentages in parenthesis. Difference in means is calculated by comparing the mean number of transactions executed after the meetings (averaged over all board meetings) vs. that for transactions executed before. The p-values for t-tests are reported in parenthesis. The symbols ***, **, and * denote statistical significance of differences at the 1%, 5%, and 10% levels, respectively. Panel B presents the distribution of the transactions on each day with respect to the board meeting date.

Panel A: Insiders Transactions Before and After the Meeting Date

	Insiders Purchases					Insiders Sales				
	Executives	Ind. Directors	Out. Blockh.	Oth. Insiders	Total	Executives	Ind. Directors	Out. Blockh.	Oth. Insiders	Total
Before D	1,771	1,696	60	1,509	5,056	42,138	11,209	1,227	4,387	58,961
	(46.1%)	(31.7%)	(60.6%)	(56.2%)	(42.1%)	(45.4%)	(43.9%)	(34.3%)	(35.6%)	(43.9%)
After D	2,074	3,647	39	1,175	6,935	50,750	14,343	2,346	7,927	75,366
	(53.9%)	(68.3%)	(39.4%)	(43.8%)	(57.9%)	(54.6%)	(56.1%)	(65.7%)	(64.4%)	(56.1%)
Diff. in	0.23	0.88***	-0.91	-1.83	1.13**	0.57**	0.81***	7.88	5.44**	1.73***
Means	(0.16)	(0.00)	(0.41)	(0.66)	(0.01)	(0.01)	(0.00)	(0.43)	(0.01)	(0.00)

Panel B: Insiders Transactions on Days Around the Meeting Date

Days	Insiders Purchases					Insiders Sales				
w.r.t. D	Executives	Ind. Directors	Out. Blockh.	Oth. Insiders	Total	Executives	Ind. Directors	Out. Blockh.	Oth. Insiders	Total
-15	112	116	2	122	352	2,356	705	123	337	3,521
-14	152	123	3	144	422	2,859	791	83	336	4,069
-13	106	118	2	162	388	2,623	675	59	328	3,685
-12	59	65	3	61	188	1,483	362	21	262	2,128
-11	68	67	29	69	233	1,318	312	12	135	1,777
-10	58	83	2	102	245	2,046	594	97	176	2,913
-9	70	127	2	142	341	3,643	635	76	211	4,565
-8	138	182	6	105	431	4,587	1,053	60	355	6,055
-7	181	178	0	147	506	4,156	1,045	78	389	5,668
-6	201	159	2	77	439	3,211	1,192	98	411	4,912
-5	112	78	2	33	225	2,247	773	84	329	3,433
-4	111	78	0	56	245	1,721	398	71	238	2,428
-3	67	75	0	84	226	2,297	524	117	155	3,093
-2	127	79	5	93	304	3,297	809	68	182	4,356
-1	209	168	2	112	491	4,294	1,341	180	543	6,358
0	**194**	**330**	**2**	**106**	**632**	**3,935**	**1,183**	**108**	**750**	**5,976**
1	249	458	1	156	864	4,523	1,313	231	706	6,773
2	126	343	4	37	510	2,655	1,095	247	545	4,542
3	132	271	0	33	436	2,414	664	120	491	3,689
4	86	166	0	87	339	2,413	821	285	591	4,110
5	129	262	4	72	467	3,403	868	89	505	4,865
6	201	329	1	108	639	4,634	1,361	68	501	6,564
7	187	281	3	94	565	4,621	1,315	195	550	6,681
8	166	242	5	79	492	4,354	1,170	183	702	6,409
9	107	167	3	45	322	2,956	821	100	377	4,254
10	97	71	3	25	196	1,776	625	108	447	2,956
11	61	85	3	69	218	1,938	429	118	137	2,622
12	91	192	2	102	387	3,065	746	169	395	4,375
13	124	219	5	112	460	3,863	822	154	615	5,454
14	124	231	3	50	408	4,200	1,110	171	615	6,096
Total	3,845	5,343	99	2,684	11,971	92,888	25,552	3,573	12,314	134,327

Panel B of Table 4.3 presents the distribution of the transactions on each day with respect to the board meeting date. The hike of executives and independent directors transactions on and after the board meeting date is very clear in this Panel. What can be also seen in this analysis is that the majority of the purchase transactions are attributed to the independent directors whereas those of outside blockholders constitute a very small portion of outside directors' sales. Therefore, in un-tabulated results we find the same pattern regarding the outside directors trades as of the independent directors.

4.4 Performance of Insider Trading Around Board Meetings

We have seen that outside directors significantly increase their trades after the board meetings. This is evidence in favor of that the outside directors trade on the information they obtain at the board meetings. However, this does not necessarily imply that the information they obtain is accurate or valuable. Indeed, Harris and Raviv (2008) note that "when outsiders control the board, insiders may not provide full or completely accurate information" (p. 1798). One way to understand whether the information obtained during board meetings is valuable or not is to analyze the trading performance of outside directors.

In analyzing trading performance, I first separate the trades into purchases and sales. This is important because, as mentioned before, purchases are more likely to be information driven whereas sales can be driven by liquidity or portfolio rebalancing motives. Therefore, purchases will be the main focus of the analysis. The whole analysis will be based on the final sample where only trades within one month window of the board meeting dates are considered [D−15,D+14]. This sample will be split into two 15-day periods based on the meeting date: Trades prior to the meeting date [D−15,D−1] and trades posterior to the meeting date [D,D+14]. I will address two questions: 1. Is there a difference between the trading performance of positions taken before and those after the board meetings? 2. Is there a difference between the trading performance of positions taken by the outside directors with respect to those of other insider groups?

4.4.1 Market Adjusted Returns for Insiders Purchases

In this section, I analyze whether outside directors profit when they purchase their company's stock around the board meetings by using a regression analysis. Following Ravina and Sapienza (2010), for each transaction made by an outside director, I calculate the market adjusted returns of holding the position for 30, 60, 90 and 180 trading days. I also report the results of 0 days holding period for demonstrative motives, however I will not be considering those cases in performance evaluation. As in most of the previous literature, market adjusted returns are computed by compounding the daily returns of a portfolio that goes long 1 dollar in the company stock mimicking the insider's purchase and short 1 dollar in the value weighted market index. In the regressions, I control for firm fixed effects to account for time-invariant firm specific characteristics. This also allows me to compare outside directors and executives belonging to the same firm.

In the basic specification, I consider outside directors purchases and I regress the return on a dummy taking value one if the trade is initiated after the board meeting. Table 4.4 reports the results of this exercise. The positive and significant intercept (in columns 1 to 5) is consistent with the literature, demonstrating that outside directors earn abnormal returns from their purchases. On average, mimicking the outside directors' buys yields a market adjusted return of 1.77% in 30 days, 1.75% in 60 days and 3.2% in 90 days, with 1% significance level. This effect is robust to controlling for the transaction size and the directors' holdings (in columns 6 to 10) to account for individuals' incentives and constraints. For a horizon of 180 days, the return is a significant 2.4%, however the significance does not persist after introducing the controls.

In order to see if there is a difference between the trading performance of positions taken before and those after the board meetings, I analyze the coefficient on the dummy variable. Table 4.4 demonstrates that in most specifications, the dummy variable has a significantly positive coefficient. This suggests that outside directors earn higher returns when they trade after attending the board meetings. The coefficient on the dummy variable is higher and more significant in the specifications with control variables, and the results get stronger as we increase the holding period. For 90 days holding period, the outside directors earn an additional 2.79% when they initiate the trade after the board meeting date, with the effect being significant at 5% level. For a horizon of 180 days, the outside directors do not gain significant returns for the trades initiated before the meetings in contrast to a significant 4.34% abnormal return for purchases after the meetings. These results are consistent with the view that outside directors

Table 4.4: **Market Adjusted Returns for Outside Directors Purchases**

This table presents the coefficient estimates of the regressions where the dependent variable is the market adjusted returns for outside directors purchases around board meetings. Market adjusted returns are computed by compounding the daily returns of a portfolio that goes long 1 dollar in the company stock mimicking the outside director's purchase and short 1 dollar in the value weighted market index, holding the position for 0, 30, 60, 90 and 180 days in respective columns. Returns are multiplied by 100 to make the coefficients in percentage form. After meeting is a dummy taking value 1 if the trade is initiated after the board meeting, and 0 otherwise. Transaction is the size of the transaction as a fraction of market capitalization (measured in $00,000). Holding is the value of the individual's holdings scaled by $10 million. Firm fixed effects are included in the regressions. The t-statistics in parentheses are estimated using standard errors adjusted for the clustering of individuals. The symbols ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)
Intercept	0.427**	1.770***	1.751***	3.176***	2.439*	0.136	1.252***	1.288*	1.682**	0.625
	(2.56)	(3.56)	(2.78)	(4.07)	(1.75)	(1.22)	(2.80)	(1.85)	(2.09)	(0.51)
After Meeting	–0.506**	0.313	1.691*	1.624	4.380**	–0.284*	0.947	2.536***	2.791**	4.344**
	(–2.12)	(0.44)	(1.93)	(1.49)	(2.21)	(–1.81)	(1.47)	(2.60)	(2.47)	(2.46)
Transaction						0.008	–0.039	–0.032	–0.053	–0.038
						(0.92)	(–1.27)	(–0.61)	(–1.26)	(–0.71)
Holdings						0.011	–0.056	0.049	0.111**	0.256**
						(1.62)	(–1.62)	(0.86)	(2.05)	(2.35)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.004	0.000	0.002	0.001	0.004	0.003	0.002	0.004	0.004	0.005
Observations	5282	5282	5282	5282	5282	3228	3228	3228	3228	3228

obtain valuable information during board meetings.

Next, I analyze the trading performance of outside directors as compared to other insider groups. The main question is how outside directors perform vis-à-vis their executive counterparts. If we find that outside directors have significantly worse trading performance than the executives, the evidence would be in favor of the argument that outside directors are kept in the dark by the executives of their firms. The analysis in this paper is especially important since I am focusing on a period around the board meetings, which constitute the basic means of bridging the informational gap between outside and inside members of the board. If the outsiders are not kept in the dark, we would expect them to perform at least as well as their executive counterparts after the board meetings.

Table 4.5 reports the results of this exercise, where I consider purchases of all insiders: executives, outside directors, and other insiders. I regress the return on a dummy taking value one if the trade is initiated by an outside director, and another dummy taking value one if the trade is initiated by a nonexecutive non-director (other) insider. The executives' coefficient is therefore captured by the intercept. In Panel A, I consider all transactions within one month window around the meeting dates. When transaction size and holdings are controlled for, executives on average earn 5.53% return in 180 days and the outside directors in the same firm obtain an amount 1.56% less over the same horizon, but the difference is not significant. Interestingly, over shorter horizons, outside directors earn higher market adjusted returns than those of the executives. However, the difference is not significant, except for the holding period of 90 days where mimicking the buys of the outside directors yields 1.84% higher return than that of the executives.

A deeper analysis where I split the sample into two subperiods with respect to the board meeting date reveals the reasons behind outperformance of the outside directors' buys. In the subperiod where only purchases prior to the meetings are considered (reported in Panel B), outside directors do not earn significantly different returns than their executive counterparts. However, the picture is altered when we constrain ourselves to trades initiated after the board meetings. Panel C reports the results in this subsample. Interestingly, executives do not earn significant market adjusted returns whereas outside directors do, with the exception of 180 days horizon. For instance, on average, an executive earns an insignificant 0.2% market adjusted return from her purchases whereas an outside director earns a significant 4.03% for 90 days horizon. For 180 days holding period, both insider groups obtain positive abnormal returns. These results suggest that

Table 4.5: **Market Adjusted Returns for Insiders Purchases**

This table presents the coefficient estimates of the regressions where the dependent variable is the market adjusted returns for insiders purchases around board meetings. Market adjusted returns are computed by compounding the daily returns of a portfolio that goes long 1 dollar in the company stock mimicking the insider's purchase and short 1 dollar in the value weighted market index, holding the position for 0, 30, 60, 90 and 180 days in respective columns. Returns are multiplied by 100 to make the coefficients in percentage form. The insiders consist of executives, outside directors, beneficial owners, affiliates, controllers, etc. Outside director is a dummy taking value 1 if the trade is initiated by an outside director, and 0 otherwise. Other insider is a dummy taking value 1 if the trade is initiated by a nonexecutive non-director insider, and 0 otherwise. Transaction is the size of the transaction as a fraction of market capitalization (measured in $00,000). Holding is the value of the individual's holdings scaled by $10 million. Panel A reports the results for one month window (-15 days to +14 days) around the board meeting date (D) whereas panels B and C split this period into two as prior vs. posterior to the board meeting. Firm fixed effects are included in the regressions. The t-statistics in parentheses are estimated using standard errors adjusted for the clustering of individuals. The symbols ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Purchases Around the Board Meetings [D−15,D+14]									
	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)
Intercept	0.260***	1.716***	0.924	1.842**	8.806***	0.093	1.572***	2.668***	2.117***	5.533***
	(2.76)	(4.90)	(1.37)	(2.45)	(5.59)	(1.07)	(4.36)	(4.59)	(3.02)	(5.62)
Out. Director (a)	–0.132	0.846	0.439	1.226	–3.176**	–0.098	0.807	0.424	1.845*	–1.561
	(–0.96)	(1.63)	(0.49)	(1.26)	(–1.98)	(–0.81)	(1.64)	(0.54)	(1.93)	(–1.19)
Oth. Insider (b)	–0.025	–0.885	–4.093**	–4.981***	–11.230**	–0.096	–1.093	–2.787	–4.728*	–7.797**
	(–0.12)	(–1.11)	(–2.21)	(–2.61)	(–2.50)	(–0.39)	(–0.91)	(–1.35)	(–1.96)	(–2.45)
Transaction						0.009	0.002	–0.011	0.112*	0.217**
						(0.55)	(0.03)	(–0.13)	(1.76)	(2.00)
Holdings						–0.001	0.115*	0.071	0.040	0.060
						(–0.22)	(1.93)	(0.79)	(0.45)	(0.54)
Transaction × (a)						–0.006	–0.038	–0.008	–0.150**	–0.247**
						(–0.36)	(–0.69)	(–0.08)	(–2.05)	(–2.09)
Holdings × (a)						0.003	–0.131**	–0.057	–0.009	0.050
						(0.46)	(–2.15)	(–0.58)	(–0.09)	(0.33)

Transaction × (b)						–0.011	–0.020	0.023	–0.112*	–0.220**
						(–0.70)	(–0.41)	(0.27)	(–1.75)	(–2.02)
Holdings × (b)						0.002	–0.120**	–0.076	–0.028	–0.045
						(0.35)	(–2.00)	(–0.84)	(–0.31)	(–0.40)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.000	0.001	0.003	0.003	0.004	0.001	0.005	0.002	0.004	0.003
Observations	11628	11628	11628	11628	11628	5603	5603	5603	5603	5603
	Panel B: Purchases Prior to the Board Meetings [D−15,D−1]									
	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)
Intercept	0.276	3.552***	–0.040	–1.049	0.539	0.074	3.088***	4.842***	3.865***	4.571***
	(1.60)	(6.29)	(–0.03)	(–0.86)	(0.38)	(0.50)	(4.64)	(4.67)	(3.17)	(2.99)
Out. Director (a)	0.193	–0.547	0.297	1.412	0.867	0.026	–0.703	–1.318	0.108	–0.864
	(0.82)	(–0.63)	(0.21)	(1.04)	(0.38)	(0.12)	(–0.85)	(–1.17)	(0.09)	(–0.39)
Oth. Insider (b)	0.049	–2.041*	–4.888	–2.887	–3.923	–0.201	–1.938	–6.960	–4.811	–3.346
	(0.14)	(–1.75)	(–1.45)	(–0.96)	(–1.59)	(–0.51)	(–0.85)	(–1.54)	(–0.90)	(–0.85)
Transaction						0.084*	–0.102	0.212	0.361	–0.522
						(1.88)	(–0.44)	(0.90)	(1.21)	(–1.30)
Holdings						–0.004	0.130**	0.047	0.045	0.065
						(–0.88)	(2.06)	(0.59)	(0.65)	(0.67)
Transaction × (a)						–0.062	0.017	–0.326	–0.596*	0.314
						(–1.35)	(0.07)	(–1.22)	(–1.86)	(0.74)
Holdings × (a)						0.003	–0.146**	–0.055	0.029	0.034
						(0.41)	(–2.18)	(–0.52)	(0.28)	(0.19)
Transaction × (b)						–0.074	0.092	–0.260	–0.485	0.410
						(–1.57)	(0.39)	(–1.04)	(–1.57)	(1.00)
Holdings × (b)						0.009**	–0.142**	–0.036	–0.028	–0.076
						(2.01)	(–2.24)	(–0.44)	(–0.37)	(–0.77)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.000	0.001	0.005	0.002	0.001	0.006	0.012	0.012	0.014	0.006
Observations	4879	4879	4879	4879	4879	2158	2158	2158	2158	2158

	Panel C: Purchases Posterior to the Board Meetings [D,D+14]									
	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)
Intercept	0.221*	0.246	1.284	3.093***	13.958***	0.036	0.557	0.801	0.207	5.010***
	(1.78)	(0.52)	(1.50)	(3.43)	(6.64)	(0.30)	(1.25)	(1.12)	(0.23)	(4.02)
Out. Director (a)	–0.267	2.065***	1.331	2.102*	–4.401**	–0.082	1.864***	2.315**	4.033***	0.254
	(–1.40)	(3.05)	(1.08)	(1.70)	(–2.23)	(–0.51)	(3.09)	(2.37)	(3.28)	(0.16)
Oth. Insider (b)	–0.028	–0.255	–3.637*	–5.764**	–18.043**	–0.351	–0.781	–0.330	–4.449*	–12.181**
	(–0.12)	(–0.24)	(–1.84)	(–2.31)	(–2.27)	(–1.06)	(–0.67)	(–0.16)	(–1.68)	(–2.20)
Transaction						–0.009	–0.011	–0.062	0.072**	0.221**
						(–0.85)	(–0.30)	(–0.87)	(1.99)	(2.27)
Holdings						0.005	0.092	0.169	0.094	0.124
						(0.29)	(0.82)	(0.96)	(0.44)	(0.56)
Transaction × (a)						0.004	–0.004	0.067	–0.073*	–0.214**
						(0.27)	(–0.09)	(0.85)	(–1.74)	(–2.14)
Holdings × (a)						0.002	–0.117	–0.134	–0.030	0.077
						(0.13)	(–1.05)	(–0.76)	(–0.14)	(0.32)
Transaction × (b)						0.007	–0.014	0.076	–0.067*	–0.223**
						(0.64)	(–0.36)	(1.08)	(–1.85)	(–2.29)
Holdings × (b)						0.011	–0.099	–0.157	–0.045	0.054
						(0.70)	(–0.88)	(–0.88)	(–0.20)	(0.22)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.005	0.003	0.006	0.008	0.001	0.008	0.005	0.009	0.006
Observations	6749	6749	6749	6749	6749	3445	3445	3445	3445	3445

high returns of outside directors are due to the information they obtain during board meetings. Therefore, board meetings help reducing the informational asymmetries between inside and outside board members.

So far I have focused on outside directors as a group. Ravina and Sapienza (2010) note that outside blockholders (nonexecutive directors who own more than 10% of the equity) should be distinguished from the rest of the outside directors that constitutes the independent directors group. Their reasoning is that outside blockholders "might have better access to information or more incentives to trade optimally, given their large stake in the company" (p. 966). In order to replicate the regressions in Ravina and Sapienza (2010), I consider only the purchases of executives and outside directors, and I use different dummies for independent directors and outside blockholders.

Table 4.6 demonstrates the results obtained from replicating the regressions in Ravina and Sapienza (2010) with the sample around the board meeting dates. As can be seen, the results are very similar to those reported in Table 4.5. The reason is that the trades made by large outside blockholders are very few with respect to other insider groups. Consistent with the previous analysis, independent directors obtain higher market adjusted returns than the executives of the same firm. The difference is not significant in the overall sample, however is significant for the subsample of purchases posterior to the board meeting date. This contradicts the findings of Ravina and Sapienza (2010) where independent directors obtain significantly less market adjusted returns than the executives. The result is driven by the outperformance of mimicking the independent directors' purchases initiated after the board meetings. This suggests that when we constrain ourselves to a more informative period (i.e., around board meetings), the independent directors do not perform worse than their executives counterparts.

As a final robustness check, I re-run the regressions of market adjusted returns for insiders purchases excluding the firm fixed effects. Even though introducing firm fixed effects is important in capturing firm specific characteristics, there is one caveat. Insiders are shown in the literature to be contrarian investors (Jenter 2005; Lakonishok and Lee 2001; Ravina and Sapienza 2010). Using firm fixed effects may inflate abnormal returns if outside directors trade after price declines and price run-ups; the level of the returns may not be positive whereas the difference with respect to an average firm is. To account for this, Table 4.7 reports the results of the specifications where firm fixed effects are not introduced. As can be seen, the results are similar to the basic case where fixed effects are included. Mimicking buys of outside directors executed after the board meetings

Table 4.6: **Market Adjusted Returns for Executives and Outside Directors Purchases**

This table presents the coefficient estimates of the regressions where the dependent variable is the market adjusted returns for insiders purchases around board meetings. Market adjusted returns are computed by compounding the daily returns of a portfolio that goes long 1 dollar in the company stock mimicking the insider's purchase and short 1 dollar in the value weighted market index, holding the position for 0, 30, 60, 90 and 180 days in respective columns. Returns are multiplied by 100 to make the coefficients in percentage form. The individuals consist of executives and outside directors (independent directors and blockholders). Independent director is a dummy taking value 1 if the trade is initiated by an independent director, and 0 otherwise. Outside blockholder is a dummy taking value 1 if the trade is initiated by a nonexecutive director that owns a minimum of 10% of the company stock, and 0 otherwise. Transaction is the size of the transaction as a fraction of market capitalization (measured in $00,000). Holding is the value of the individual's holdings scaled by $10 million. Panel A reports the results for one month window (-15 days to +14 days) around the board meeting date (D) whereas panels B and C split this period into two as prior vs. posterior to the board meeting. Firm fixed effects are included in the regressions. The t-statistics in parentheses are estimated using standard errors adjusted for the clustering of individuals. The symbols ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Purchases Around the Board Meetings [D−15,D+14]									
	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)
Intercept	0.211**	2.281***	3.320***	3.511***	7.295***	0.083	1.357***	2.614***	1.806***	4.614***
	(2.45)	(6.83)	(5.71)	(5.45)	(6.84)	(0.98)	(3.88)	(4.81)	(2.78)	(4.87)
Ind. Director (a)	–0.154	0.777	0.368	1.218	–2.511	–0.059	0.736	0.284	1.903**	–1.504
	(–1.09)	(1.46)	(0.41)	(1.23)	(–1.61)	(–0.48)	(1.48)	(0.36)	(1.98)	(–1.14)
Out. Blockholder (b)	0.724	–5.411	–4.869	–4.972	–23.727***	0.133	–1.410	–4.029	–4.999	–16.786
	(1.31)	(–1.60)	(–1.00)	(–1.10)	(–2.74)	(0.15)	(–0.26)	(–0.46)	(–0.62)	(–1.41)
Transaction						0.009	0.007	–0.008	0.119*	0.225**
						(0.55)	(0.14)	(–0.09)	(1.82)	(2.04)
Holdings						–0.001	0.123*	0.072	0.039	0.062
						(–0.20)	(1.94)	(0.78)	(0.43)	(0.54)
Transaction × (a)						–0.026	–0.014	0.112	–0.031	–0.076
						(–0.95)	(–0.21)	(1.01)	(–0.31)	(–0.51)
Holdings × (a)						0.012	–0.142**	–0.001	0.118	0.290*
						(1.41)	(–2.18)	(–0.01)	(1.16)	(1.91)

Transaction × (b)						0.001	–0.051	–0.033	–0.172**	–0.249*
						(0.05)	(–0.87)	(–0.35)	(–2.11)	(–1.95)
Holdings × (b)						–0.003	–0.107	–0.068	–0.074	–0.035
						(–0.17)	(–0.90)	(–0.51)	(–0.51)	(–0.16)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.002	0.001	0.001	0.004	0.001	0.004	0.002	0.003	0.004
Observations	8979	8979	8979	8979	8979	5073	5073	5073	5073	5073

Panel B: Purchases Prior to the Board Meetings [D−15,D−1]										
	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)
Intercept	0.173	4.152***	3.350***	1.659**	1.321	0.100	3.210***	4.727***	3.954***	4.706***
	(1.31)	(8.74)	(4.54)	(2.04)	(0.94)	(0.71)	(5.44)	(6.36)	(4.68)	(3.23)
Ind. Director (a)	0.233	–0.891	–0.016	1.207	1.738	0.073	–1.048	–1.369	0.304	–0.667
	(0.95)	(–0.96)	(–0.01)	(0.88)	(0.73)	(0.32)	(–1.25)	(–1.27)	(0.26)	(–0.29)
Out. Blockholder (b)	0.184	–5.902	–12.191	–15.700**	–25.395**	0.447	–9.552	–15.910	–24.649*	–21.393
	(0.19)	(–1.09)	(–1.30)	(–2.11)	(–2.07)	(0.26)	(–0.88)	(–0.88)	(–1.72)	(–1.16)
Transaction						0.082*	–0.045	0.279	0.436	–0.469
						(1.85)	(–0.19)	(1.18)	(1.47)	(–1.15)
Holdings						–0.004	0.131**	0.041	0.037	0.053
						(–0.92)	(2.05)	(0.51)	(0.54)	(0.56)
Transaction × (a)						–0.063	–0.003	–0.308	–0.626*	0.461
						(–1.36)	(–0.01)	(–1.23)	(–1.84)	(1.10)
Holdings × (a)						0.013	–0.182**	0.098	0.262**	0.467**
						(1.07)	(–2.28)	(0.66)	(2.26)	(2.46)
Transaction × (b)						–0.049	–0.086	–0.410	–0.756**	0.243
						(–1.02)	(–0.31)	(–1.23)	(–2.26)	(0.52)
Holdings × (b)						–0.045	0.056	–0.033	0.722	–0.396
						(–0.69)	(0.13)	(–0.05)	(1.33)	(–0.36)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.002	0.004	0.006	0.007	0.007	0.018	0.015	0.027	0.014
Observations	3390	3390	3390	3390	3390	1878	1878	1878	1878	1878

	Panel C: Purchases Posterior to the Board Meetings [D,D+14]									
	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)
Intercept	0.217*	0.906*	2.906***	4.101***	10.492***	0.013	0.200	0.646	–0.404	3.468***
	(1.69)	(1.94)	(3.41)	(4.92)	(8.49)	(0.11)	(0.44)	(0.89)	(–0.45)	(2.87)
Ind. Director (a)	–0.304	1.944***	1.284	2.208*	–3.814**	–0.040	1.749***	2.022**	4.044***	0.198
	(–1.54)	(2.84)	(1.02)	(1.77)	(–2.12)	(–0.24)	(2.88)	(2.06)	(3.27)	(0.12)
Out. Blockholder (b)	1.077*	–4.726	–3.416	–0.849	–23.063**	–0.737	7.692	10.675	11.681	–4.136
	(1.71)	(–0.96)	(–0.62)	(–0.16)	(–2.09)	(–0.48)	(1.16)	(0.90)	(1.05)	(–0.28)
Transaction						–0.008	–0.011	–0.061	0.075**	0.223**
						(–0.82)	(–0.28)	(–0.86)	(2.03)	(2.28)
Holdings						0.004	0.106	0.174	0.091	0.107
						(0.20)	(0.87)	(0.93)	(0.40)	(0.45)
Transaction × (a)						–0.041	0.057	0.244**	0.049	–0.124
						(–1.10)	(0.80)	(2.25)	(0.47)	(–0.79)
Holdings × (a)						0.002	–0.114	–0.106	0.028	0.189
						(0.11)	(–0.94)	(–0.56)	(0.12)	(0.71)
Transaction × (b)						–0.026	–0.059	0.152	0.008	–0.038
						(–1.45)	(–0.89)	(1.35)	(0.09)	(–0.25)
Holdings × (b)						2.211***	1.340	–7.875**	–6.628**	–8.753*
						(2.69)	(0.63)	(–2.38)	(–2.25)	(–1.83)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.002	0.006	0.001	0.002	0.004	0.004	0.006	0.006	0.007	0.003
Observations	5589	5589	5589	5589	5589	3195	3195	3195	3195	3195

Table 4.7: **Market Adjusted Returns for Insiders Purchases: Without Firm Fixed Effects**

This table presents the coefficient estimates of the regressions where the dependent variable is the market adjusted returns for insiders purchases around board meetings. Market adjusted returns are computed by compounding the daily returns of a portfolio that goes long 1 dollar in the company stock mimicking the insider's purchase and short 1 dollar in the value weighted market index, holding the position for 0, 30, 60, 90 and 180 days in respective columns. Returns are multiplied by 100 to make the coefficients in percentage form. The insiders consist of executives, outside directors, beneficial owners, affiliates, controllers, etc. Outside director is a dummy taking value 1 if the trade is initiated by an outside director, and 0 otherwise. Other insider is a dummy taking value 1 if the trade is initiated by a nonexecutive non-director insider, and 0 otherwise. Transaction is the size of the transaction as a fraction of market capitalization (measured in $00,000). Holding is the value of the individual's holdings scaled by $10 million. Panel A reports the results for one month window (-15 days to +14 days) around the board meeting date (D) whereas panels B and C split this period into two as prior vs. posterior to the board meeting. The t-statistics in parentheses are estimated using standard errors adjusted for the clustering of individuals. The symbols ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Purchases Around the Board Meetings [D−15,D+14]									
	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)
Intercept	0.194*	3.654***	4.317***	4.001*	5.858*	0.180**	1.830***	2.758***	2.745***	4.817***
	(1.93)	(3.47)	(3.43)	(1.75)	(1.87)	(2.04)	(3.64)	(3.96)	(3.06)	(3.89)
Out. Director (a)	–0.108	–1.673	–1.426	0.270	–0.466	–0.251**	0.104	0.222	0.654	–1.189
	(–0.76)	(–1.47)	(–1.00)	(0.11)	(–0.12)	(–2.38)	(0.17)	(0.27)	(0.62)	(–0.75)
Oth. Insider (b)	0.217	–4.372**	–15.268***	–12.554***	–3.693	–0.431**	1.197	–1.827	–3.349	0.627
	(1.05)	(–2.34)	(–3.25)	(–3.05)	(–0.82)	(–2.32)	(0.74)	(–0.72)	(–1.40)	(0.16)
Transaction						0.000	0.047	0.050	0.050	0.030
						(0.04)	(1.18)	(0.75)	(1.03)	(0.34)
Holdings						0.001	0.057**	–0.043*	–0.167***	–0.175***
						(0.21)	(2.09)	(–1.93)	(–5.79)	(–4.25)
Transaction × (a)						0.036***	–0.144**	–0.119	–0.068	–0.144
						(2.62)	(–2.30)	(–0.99)	(–0.64)	(–1.12)
Holdings × (a)						–0.018**	–0.074*	0.156***	0.407***	0.424***
						(–2.09)	(–1.75)	(3.13)	(4.93)	(4.96)

Transaction × (b)						0.006	–0.060	–0.060	–0.052	–0.029
						(0.56)	(–1.50)	(–0.88)	(–1.08)	(–0.33)
Holdings × (b)						0.001	–0.084***	0.036	0.163***	0.149***
						(0.26)	(–2.70)	(1.22)	(4.33)	(3.07)
Fixed Effects	No	No	No	No	No	No	No	No	No	No
R-squared	0.002	0.010	0.069	0.035	0.001	0.011	0.004	0.002	0.006	0.002
Observations	11628	11628	11628	11628	11628	5603	5603	5603	5603	5603
Panel B: Purchases Prior to the Board Meetings [D−15,D−1]										
	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)
Intercept	0.285	5.740***	3.608*	0.211	0.264	0.225	2.913***	4.541***	5.477***	6.855***
	(1.63)	(2.95)	(1.78)	(0.07)	(0.08)	(1.56)	(3.43)	(4.18)	(3.64)	(3.34)
Out. Director (a)	0.012	–4.196**	–0.950	3.471	2.876	–0.125	–0.846	–1.516	–2.331	–4.109*
	(0.05)	(–2.07)	(–0.44)	(1.12)	(0.75)	(–0.71)	(–0.84)	(–1.16)	(–1.37)	(–1.68)
Oth. Insider (b)	0.229	–4.996*	–15.402***	–9.392**	–5.342	–0.540*	–0.891	–5.925**	–8.478***	–9.162**
	(0.88)	(–1.77)	(–3.25)	(–2.27)	(–1.06)	(–1.83)	(–0.48)	(–2.39)	(–2.92)	(–2.31)
Transaction						0.066**	0.215	0.671***	0.446*	–0.249
						(2.53)	(0.96)	(3.04)	(1.82)	(–0.70)
Holdings						0.004	0.093***	–0.084**	–0.229***	–0.232***
						(1.40)	(3.01)	(–2.27)	(–5.57)	(–6.29)
Transaction × (a)						–0.028	–0.356	–0.761***	–0.575**	0.024
						(–1.02)	(–1.54)	(–3.18)	(–2.15)	(0.06)
Holdings × (a)						–0.033***	–0.062	0.217***	0.421***	0.379***
						(–4.26)	(–1.54)	(2.70)	(3.72)	(2.68)
Transaction × (b)						–0.068**	–0.247	–0.707***	–0.482*	0.234
						(–2.57)	(–1.09)	(–3.20)	(–1.96)	(0.65)
Holdings × (b)						–0.002	–0.102***	0.091**	0.231***	0.225***
						(–0.55)	(–3.20)	(2.33)	(5.23)	(5.51)
Fixed Effects	No	No	No	No	No	No	No	No	No	No
R-squared	0.001	0.017	0.092	0.042	0.007	0.012	0.010	0.024	0.022	0.007
Observations	4879	4879	4879	4879	4879	2158	2158	2158	2158	2158

						Panel C: Purchases Posterior to the Board Meetings [D,D+14]				
	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)
Intercept	0.119	1.936***	4.901***	7.123***	10.468***	0.095	0.896*	0.847	0.278	3.444**
	(0.93)	(2.72)	(3.85)	(2.85)	(2.78)	(0.86)	(1.66)	(1.08)	(0.30)	(2.38)
Out. Director (a)	–0.135	0.256	–1.897	–2.568	–3.988	–0.251*	0.976	2.113**	3.249***	0.622
	(–0.79)	(0.28)	(–1.21)	(–0.96)	(–0.80)	(–1.93)	(1.47)	(2.19)	(2.75)	(0.31)
Oth. Insider (b)	0.160	–4.529*	–14.770***	–14.869***	0.996	–0.355*	4.423**	3.287	1.615	10.578
	(0.56)	(–1.81)	(–2.86)	(–3.00)	(0.17)	(–1.65)	(2.34)	(0.94)	(0.48)	(1.56)
Transaction						–0.009	0.027	–0.035	–0.000	0.075
						(–1.13)	(1.21)	(–1.15)	(–0.01)	(0.92)
Holdings						–0.005	–0.008	0.019	–0.073	–0.089
						(–0.90)	(–0.24)	(0.32)	(–0.95)	(–0.81)
Transaction × (a)						0.045***	–0.105	–0.025	0.030	–0.141
						(3.01)	(–1.38)	(–0.17)	(0.20)	(–1.09)
Holdings × (a)						–0.002	–0.051	0.077	0.396***	0.486***
						(–0.21)	(–1.13)	(1.12)	(2.87)	(3.67)
Transaction × (b)						0.016*	–0.037	0.027	–0.003	–0.080
						(1.74)	(–1.61)	(0.85)	(–0.06)	(–0.95)
Holdings × (b)						0.027**	–0.170**	–0.093	0.122	0.073
						(2.23)	(–2.46)	(–0.84)	(0.70)	(0.36)
Fixed Effects	No	No	No	No	No	No	No	No	No	No
R-squared	0.001	0.014	0.049	0.030	0.002	0.017	0.008	0.003	0.007	0.005
Observations	6749	6749	6749	6749	6749	3445	3445	3445	3445	3445

continue yielding higher market adjusted returns as compared to the executives when transaction size and holdings are controlled for. The effect is significant for most horizons. Overall, results indicate that outside directors learn a lot about their firms at the board meetings, and this effect is robust to many specifications.

4.4.2 Market Adjusted Returns for Insiders Sales

In this section, I analyze whether outside directors profit when they sell their company's stock around the board meetings by using the same method as in the previous section. Market adjusted returns are computed by compounding the daily returns of a portfolio that goes short 1 dollar in the company stock mimicking the insider's sale and long 1 dollar in the value weighted market index.

In the basic specification, I consider outside directors sales and I regress the return on a dummy taking value one if the trade is initiated after the board meeting. Table 4.8 reports the results of this exercise. The negative and significant intercepts are consistent with Ravina and Sapienza (2010) which documents that independent directors obtain significantly negative abnormal returns from their sales. On average, mimicking the outside directors' sells yields a market adjusted return of -0.75% in 30 days, -1.50% in 60 days and -2.07% in 90 days and -6-09% in 180 days; all with high statistical significance (in columns 1 to 5). This effect is robust to controlling for the transaction size and the directors' holdings (in columns 6 to 10) to account for individuals' incentives and constraints. Nevertheless, the fact that the sale is executed after the board meetings increases the abnormal returns. Indeed, for 90 days horizon, mimicking outside directors' sells initiated after the meetings yields a significant 0.82% market adjusted return when controls are included. This demonstrates that the informativeness of the board meetings is even documented in outside directors' sales which may be driven largely by other motives.

Finally, I analyze the trading performance of outside directors' sales vis-à-vis their executive counterparts. Considering sales transactions of all insiders, I regress the return on a dummy taking value one if the trade is initiated by an outside director, and another dummy taking value one if the trade is initiated by other insider. The executives' coefficient is therefore captured by the intercept. No matter the trade is initiated before or after the meeting, executives always obtain significantly positive market adjusted returns from their sales transactions, except for 180 days horizon. This is in contradiction

Table 4.8: **Market Adjusted Returns for Outside Directors Sales**

This table presents the coefficient estimates of the regressions where the dependent variable is the market adjusted returns for outside directors sales around board meetings. Market adjusted returns are computed by compounding the daily returns of a portfolio that goes short 1 dollar in the company stock mimicking the outside director's sale and long 1 dollar in the value weighted market index, holding the position for 0, 30, 60, 90 and 180 days in respective columns. Returns are multiplied by 100 to make the coefficients in percentage form. After meeting is a dummy taking value 1 if the trade is initiated after the board meeting, and 0 otherwise. Transaction is the size of the transaction as a fraction of market capitalization (measured in $00,000). Holding is the value of the individual's holdings scaled by $10 million. Firm fixed effects are included in the regressions. The t-statistics in parentheses are estimated using standard errors adjusted for the clustering of individuals. The symbols ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)
Intercept	–0.055	–0.753**	–1.507***	–2.073***	–6.099***	–0.178***	–0.015	–0.707*	–0.777*	–2.974***
	(–1.00)	(–2.57)	(–4.44)	(–4.05)	(–8.31)	(–3.64)	(–0.06)	(–1.94)	(–1.82)	(–5.04)
After Meeting	–0.142*	0.003	0.019	1.729**	1.074	–0.137*	0.425	0.634	1.591**	0.269
	(–1.66)	(0.01)	(0.04)	(2.23)	(0.97)	(–1.76)	(1.13)	(1.12)	(2.40)	(0.31)
Transaction						0.004***	0.003	0.003	0.005	–0.004
						(3.08)	(0.74)	(0.44)	(0.83)	(–0.62)
Holdings						–0.000	–0.001*	0.005***	0.007***	0.011***
						(–0.03)	(–1.79)	(5.32)	(4.37)	(4.00)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.000	0.000	0.002	0.000	0.003	0.001	0.003	0.006	0.007
Observations	28965	28965	28965	28965	28965	6062	6062	6062	6062	6062

Table 4.9: **Market Adjusted Returns for Insiders Sales**

This table presents the coefficient estimates of the regressions where the dependent variable is the market adjusted returns for insiders sales around board meetings. Market adjusted returns are computed by compounding the daily returns of a portfolio that goes short 1 dollar in the company stock mimicking the insider's sale and long 1 dollar in the value weighted market index, holding the position for 0, 30, 60, 90 and 180 days in respective columns. Returns are multiplied by 100 to make the coefficients in percentage form. The insiders consist of executives, outside directors, beneficial owners, affiliates, controllers, etc. Outside director is a dummy taking value 1 if the trade is initiated by an outside director, and 0 otherwise. Other insider is a dummy taking value 1 if the trade is initiated by a nonexecutive non-director insider, and 0 otherwise. Transaction is the size of the transaction as a fraction of market capitalization (measured in $00,000). Holding is the value of the individual's holdings scaled by $10 million. Panel A reports the results for one month window (-15 days to +14 days) around the board meeting date (D) whereas panels B and C split this period into two as prior vs. posterior to the board meeting. Firm fixed effects are included in the regressions. The t-statistics in parentheses are estimated using standard errors adjusted for the clustering of individuals. The symbols ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Sales Around the Board Meetings [D−15,D+14]									
	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)
Intercept	–0.150***	0.081	0.169	0.776***	–3.184***	–0.418***	0.712***	0.848***	1.358***	–0.907***
	(–5.53)	(0.63)	(0.81)	(3.05)	(–10.40)	(–22.26)	(8.19)	(5.81)	(7.60)	(–3.55)
Out. Director (a)	0.045	–0.366	–0.586	–0.807	–1.220	0.175***	–0.600***	–1.091***	–0.948**	–2.003***
	(0.63)	(–1.15)	(–0.94)	(–1.11)	(–1.35)	(4.16)	(–2.92)	(–3.22)	(–2.26)	(–3.31)
Oth. Insider (b)	–0.068	–1.235	–1.981*	–3.306**	–1.787	0.217**	–0.905**	–2.190***	–3.414***	–4.235**
	(–0.55)	(–1.47)	(–1.89)	(–2.43)	(–1.30)	(2.33)	(–1.99)	(–2.65)	(–3.34)	(–2.46)
Transaction						0.001	–0.006**	–0.007	0.001	–0.000
						(1.33)	(–2.17)	(–1.18)	(0.09)	(–0.00)
Holdings						0.000***	–0.000	0.000	0.001	0.001
						(3.60)	(–0.06)	(0.40)	(0.44)	(0.40)
Transaction × (a)						0.002	–0.002	–0.006	–0.017	–0.018
						(1.32)	(–0.38)	(–0.70)	(–1.35)	(–1.43)
Holdings × (a)						–0.000**	–0.001**	0.002***	0.003**	0.005***
						(–2.17)	(–2.18)	(3.04)	(2.57)	(4.22)

Transaction × (b)						–0.001	0.005	0.003	–0.008	–0.008
						(–0.94)	(1.55)	(0.44)	(–0.87)	(–0.76)
Holdings × (b)						–0.000**	0.002	0.006**	0.006**	0.016***
						(–2.39)	(1.54)	(2.36)	(2.15)	(3.37)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.000	0.001	0.001	0.001	0.000	0.002	0.001	0.002	0.002	0.003
Observations	133199	133199	133199	133199	133199	25713	25713	25713	25713	25713
Panel B: Sales Prior to the Board Meetings [D−15,D−1]										
	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)
Intercept	–0.050	–0.279*	0.017	0.751**	–3.173***	–0.389***	0.692***	0.834***	1.522***	–0.014
	(–1.13)	(–1.80)	(0.07)	(2.41)	(–7.78)	(–13.71)	(5.43)	(3.93)	(5.87)	(–0.04)
Out. Director (a)	0.037	0.042	0.267	–0.128	–1.842	0.088	–0.630**	–0.847*	–0.911	–2.771***
	(0.30)	(0.09)	(0.31)	(–0.12)	(–1.41)	(1.32)	(–2.08)	(–1.71)	(–1.43)	(–3.33)
Oth. Insider (b)	0.128	0.148	–0.094	–0.208	–2.672	0.361**	–0.461	–1.818	–2.294	–6.898***
	(0.80)	(0.15)	(–0.07)	(–0.13)	(–1.29)	(2.46)	(–0.57)	(–1.30)	(–1.35)	(–2.79)
Transaction						0.000	–0.007	–0.005	0.012	0.020
						(0.24)	(–1.32)	(–0.53)	(1.00)	(1.40)
Holdings						0.000***	0.001*	0.001	0.000	0.001
						(2.79)	(1.77)	(0.86)	(0.24)	(0.77)
Transaction × (a)						0.004	–0.001	–0.002	–0.018	–0.028
						(1.59)	(–0.08)	(–0.18)	(–1.09)	(–1.46)
Holdings × (a)						–0.000	–0.000	0.003***	0.003***	0.005***
						(–0.78)	(–1.15)	(4.41)	(4.48)	(5.23)
Transaction × (b)						0.001	–0.000	–0.001	–0.024*	–0.043
						(0.50)	(–0.01)	(–0.06)	(–1.70)	(–1.57)
Holdings × (b)						–0.001***	0.001	0.002	0.002	0.007*
						(–4.03)	(0.33)	(1.43)	(0.68)	(1.70)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.000	0.000	0.000	0.000	0.001	0.002	0.001	0.002	0.001	0.004
Observations	58376	58376	58376	58376	58376	11410	11410	11410	11410	11410

	Panel C: Sales Posterior to the Board Meetings [D,D+14]									
	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)	RET(t)	RET(t+30)	RET(t+60)	RET(t+90)	RET(t+180)
Intercept	–0.252***	0.239	0.099	0.611*	–3.499***	–0.434***	0.724***	0.860***	1.161***	–1.684***
	(–8.71)	(1.59)	(0.41)	(1.96)	(–9.80)	(–18.39)	(6.92)	(5.22)	(5.65)	(–5.34)
Out. Director (a)	0.049	–0.522	–0.821	–1.093	0.137	0.211***	–0.566**	–1.269***	–0.960*	–1.202
	(0.68)	(–1.43)	(–1.37)	(–1.52)	(0.14)	(4.08)	(–2.22)	(–3.15)	(–1.93)	(–1.63)
Oth. Insider (b)	0.050	–1.129	–2.066*	–3.710**	–0.279	0.110	–1.294**	–2.548***	–2.993***	–1.720
	(0.46)	(–1.47)	(–1.85)	(–2.36)	(–0.19)	(0.88)	(–2.48)	(–2.76)	(–2.64)	(–0.91)
Transaction						0.002	–0.008	–0.014**	–0.015***	–0.018***
						(1.32)	(–1.64)	(–2.46)	(–2.95)	(–2.65)
Holdings						0.000***	–0.001*	0.000	0.002	0.001
						(2.60)	(–1.69)	(0.26)	(0.62)	(0.20)
Transaction × (a)						–0.001	0.002	–0.006	–0.008	–0.015
						(–0.33)	(0.35)	(–0.42)	(–0.57)	(–0.73)
Holdings × (a)						–0.000***	–0.001	0.002*	0.002	0.004**
						(–3.66)	(–1.02)	(1.82)	(1.10)	(2.05)
Transaction × (b)						–0.002	0.007	0.005	0.001	0.001
						(–1.58)	(1.43)	(0.98)	(0.16)	(0.19)
Holdings × (b)						0.000	0.004**	0.009***	0.009**	0.023***
						(0.01)	(2.56)	(2.98)	(2.49)	(4.34)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.000	0.001	0.001	0.002	0.000	0.002	0.002	0.003	0.002	0.002
Observations	74823	74823	74823	74823	74823	14303	14303	14303	14303	14303

with Ravina and Sapienza (2010) where they are shown to obtain negative abnormal returns. This suggests that around the board meetings, executives sells are informative. This may be due to the fact that executives gather information around the board meetings, hence their sales in these periods are more likely to be information driven. However, outside directors obtain significantly lower returns than their firms' executives, even after the board meetings.

Overall, the findings in this section is consistent with the literature which documents that sales may be driven by diversification or liquidity motives rather than information (Jeng, Metrick, and Zeckhauser 2003; Lakonishok and Lee 2001; Ravina and Sapienza 2010). This seems to be the case especially for outside directors. One caution is that analyzing a period around the board meetings introduces further noise since awards and grants are more likely to be transferred to insiders during the board meetings. Insiders may opt to sell these stocks right after the meetings due to the previously mentioned motives.

4.5 Concluding Remarks

This paper analyzes the information content of the board meetings from the point of view of the outside directors. I focus on insider purchases, since these trades have proven to be information driven in the literature. The first finding is that insider trading significantly increases around board meetings. The executives trade extensively shortly before and after the board meetings, whereas outside directors increase their trading frequency significantly after the meetings. Consistent with the literature, abnormal returns to outside directors purchases are positive around the board meetings. Interestingly, outside directors earn significantly higher returns when they trade after acquiring information at the board meetings. As compared to the performance of their executive counterparts, outside directors who purchase company stock before the board meetings do not perform better, however those who trade after the meetings gain significantly higher abnormal returns. Overall, the evidence presented in this paper suggests that board meetings are important in outside directors' information acquisition: Outsiders do learn a lot about their firms at annual board meetings.

Many interesting extensions of this study are available. First of all, as in the rest of the literature, this paper fails to associate insider sales with consistently well trading performance. One reason could be the awards and grants granted during the board meetings. If one could classify the individuals as those who receive awards and options, and those who don't, transactions of the non-receivers might provide relevant information on the future of the firm. This is open to investigation since the TFN Insider Filing database provides this information. Second, one can try to understand information content of board meetings during bad times for the company. Just as Vafeas (1999) demonstrates that the frequency of board meetings is higher in bad times, so would be the information contained in each meeting. Moreover, it might be possible that the outside directors not only use this information for their own (insider) trading; but also share it with outsiders to be used in further (outsider) trading. This subject deserves attention. Finally, I have only focused on insider trading around the board meeting dates to evaluate the information content of the meetings. There are other manners to explore this subject, such as analyzing trading volume or bidask spread of company stocks around the board meeting dates.

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